A reformulation of the FLQ approach to computing regional input–output coefficients

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ABSTRACT

In this paper, we examine alternative methods of computing regional input–output (IO) coefficients, with an emphasis on their relative accuracy and the complexity of the computations required. We propose a novel way of implementing the well-known FLQ (Flegg's location quotient) approach. Although the FLQ formula often yields very satisfactory results, the need to specify values of the unknown parameter δ in this formula presents an obstacle to its implementation. Here we develop a fresh approach to the use of the FLQ that substantially simplifies its application, while simultaneously enhancing its performance. We focus on how regional size, R, is incorporated in this formula and simplify the way in which R affects the allowance made for imports from other regions. We call this new formula the *reformulated* FLQ or RFLQ. We also show how the unknown parameter in the RFLQ can be computed. We test our proposal using the 2005 and 2015 Korean survey-based interregional IO datasets and contrast our estimates with both survey-based values and the results from several other techniques. We also examine two different information scenarios: with and without industry-specific information. The results suggest that the RFLQ can yield more accurate estimates of regional IO coefficients, and in a more straightforward way, than is possible with the traditional FLQ.

Keywords Regional input–output tables; non-survey methods; FLQ; RFLQ; 2D-LQ

1 INTRODUCTION

1.1 Location quotients and regional input-output models

Location quotients (LQs) are still a widely used non-survey technique to regionalize national input–output (IO) tables and to generate interregional IO (IRIO) models. Their principal attraction is the minimal data requirements, namely regional and national output (or employment) by sector. Many different LQ-based formulae have been developed, which are discussed in detail in Flegg et al. (2021) and in several other papers. The most basic formula is the *simple* LQ:

$$SLQ_i = \frac{\frac{x_i^r}{x_\bullet^r}}{\frac{x_i^n}{x_\bullet^n}} = \frac{\frac{x_i^r}{x_i^n}}{\frac{x_\bullet^r}{x_\bullet^n}} = \frac{wx_i^r}{wx^r} \quad (1)$$

Here x_i^r and x_i^n are the total output (production) of the *i*th regional and national sector, respectively, while $x_\bullet^r$ and $x_\bullet^n$ are the corresponding regional and national aggregates. wx_i^r represents the weight of regional sector *i* in the national economy, whereas wx^r represents the weight of region *r* in the national economy, i.e., its relative size. SLQ_i measures the degree of specialization of region *r* in sector *i* relative to the nation. The regional input coefficients are derived according to the following rule:

$$\hat{a}_{ij}^r = \begin{cases} a_{ij}^n SLQ_i & if \quad SLQ_i < 1 \\ a_{ij}^n & if \quad SLQ_i \geq 1 \end{cases} \quad (2)$$

where $\hat{a}_{ij}^r$ is the estimated regional input coefficient and a_{ij}^n is the corresponding observed national input coefficient (excluding inputs purchased from abroad).

However, it has long been known that the SLQ tends to understate a region's imports from other regions; this occurs because the SLQ rules out any 'cross-hauling' (Stevens et al., 1989). Cross-hauling takes place when a region simultaneously imports and exports a given commodity. For a systematic treatment of this issue, see Többen and Kronenberg (2015).

The *cross-industry* LQ was one of the first refinements of the SLQ, as it considers the relative size of both supplying sector *i* and purchasing sector *j*. The formula is as follows:

$$CILQ_{ij} = \frac{SLQ_i}{SLQ_j} = \frac{x_i^r / x_i^n}{x_j^r / x_j^n} \quad (3)$$

where the constraints are applied as in (2). Unlike the SLQ, however, the CILQ applies a cell-by-cell adjustment. This means that it does, in principle at least, deal with the problem of cross-hauling. What it does not do is to consider the relative size of a region, $x_\bullet^r/x_\bullet^n$, which cancels out in formula (3). By contrast, this ratio remains a component of the SLQ formula (1).

Round (1978) argues that any adjustment formula should incorporate three elements: (i) the relative size of the supplying sector *i*, (ii) the relative size of the purchasing sector *j* and (iii) the relative size of the region. The CILQ satisfies (i) and (ii) but not (iii), whereas the SLQ satisfies (i) and (iii) but not (ii). Round therefore suggests the following formula, which simultaneously satisfies all three requirements:

$$RLQ_{ij} = \frac{SLQ_i}{\log_2(1 + SLQ_j)} \tag{4}$$

Nonetheless, Flegg et al. (1995) criticize the SLQ and RLQ on the grounds that both would tend to understate the imports of relatively small regions owing to the way in which the ratio $x_{\bullet}^r / x_{\bullet}^n$ is implicitly incorporated in each formula. The FLQ aims to correct this shortcoming.

The crucial hypothesis underpinning the FLQ is that a region's propensity to import from other domestic regions is inversely and nonlinearly related to its relative size. By incorporating explicit adjustments for regional size, the FLQ should yield more precise estimates of regional input coefficients and hence multipliers. Along with other non-survey methods, the FLQ aims to offer regional analysts a means by which they can build regional tables that reflect, as closely as possible, each region's economic structure. See, for example, the application to Mexican regions by Dávila-Flores (2015) and to Chilean regions by Mardones and Silva (2021).

The FLQ is defined as follows (cf. Flegg and Webber, 1997):

$$FLQ_{ij} = \begin{cases} \lambda CILQ_{ij} & \text{for } i \neq j \\ \lambda SLQ_i & \text{for } i = j \end{cases} \tag{5}$$

where λ captures a region's relative size. This scalar is defined as follows:

$$\lambda = [\log_2(1 + \frac{x_{\bullet}^r}{x_{\bullet}^n})]^{\delta} \tag{6}$$

Here $0 \leq \delta < 1$ is a parameter that controls the degree of convexity in equation (6). The larger the value of δ, the lower the value of λ, and the greater the allowance for extra regional imports. The FLQ formula is implemented just like other LQ methods, as in equation (2).

A variant of the FLQ is the *augmented* FLQ (AFLQ), which takes regional specialization into account. It is defined as follows (cf. Flegg and Webber, 2000):

$$AFLQ_{ij} = FLQ_{ij}[\log_2(1 + SLQ_j)] \tag{7}$$

which is applicable only when $SLQ_j > 1$.

The AFLQ approach was successfully employed by Mastronardi et al. (2022) in constructing a bi-regional input-output matrix for Argentina, which separated the city of Buenos Aires from the rest of the country. However, the FLQ could have been used instead in this study since the AFLQ and FLQ often yield very similar outcomes (Flegg et al., 2016; Lampiris et al., 2020).

Several case studies, including Flegg and Tohmo (2016), have demonstrated that the FLQ can yield more accurate results than the SLQ and CILQ. This evidence is corroborated by the Monte Carlo study of Bonfiglio and Chelli (2008). A similar methodological approach is taken by Mardones and Silva (2023). On the other hand, Lamonica and Chelli (2018) find that the FLQ performs better than the SLQ in smaller regions, yet worse in larger regions. The FLQ is strongly criticized by Fujimoto (2019) on both conceptual and empirical grounds. A response to these criticisms is given in Flegg et al. (2021). Finally, we may note that the FLQ's use in a multiregional context is examined by Hermannsson (2016), Jahn (2017), Jahn et al. (2020), and Garcia-Hernandez and Brouwer (2021).

In a recent contribution, Kwon and Choi (2023) identify an apparent shortcoming of the FLQ. They focus on the CILQ component of the formula and consider situations where $SLQ_i < 1$ and $SLQ_j < 1$. If $SLQ_i < SLQ_j$, then $CILQ_{ij} < 1$ and the national input coefficient will be adjusted downwards, whereas if $SLQ_i > SLQ_j$, no adjustment will be made. The authors argue that a failure to adjust the national coefficient in this case would represent a distortion, which could be corrected by using SLQ_i as the scalar. Proceeding in this way, the authors find that their proposed KFLQ formula yields enhanced results. However, the CILQ component of the FLQ would no longer represent the relative size of the supplying and purchasing sectors in such cases and its rationale would be lost.

More fundamentally, Pereira-López et al. (2020) propose a two-dimensional approach (2D-LQ) to estimate domestic coefficients at the sub-territorial level. This technique can be extrapolated to other contexts; for instance, generating intermediate flow matrices. In this approach, estimates of regional coefficients are calculated according to the following rule:

$$\widetilde{\mathbf{A}}^R = \hat{\mathbf{r}}(\alpha)\mathbf{A}^N\hat{\mathbf{s}}(\beta) \tag{8}$$

where $\mathbf{A}$ is a matrix of intermediate domestic coefficients, and $\hat{\mathbf{r}}(\alpha)$ and $\hat{\mathbf{s}}(\beta)$ are diagonal matrices whose main diagonal elements work as weighting factors. Scalars α and β are the parameters influencing row and column rectifications, respectively. As in the CILQ, RLQ and FLQ, row and column corrections are addressed differently:

$$\mathbf{r}(\alpha) = \begin{cases} (SLQ_i)^{\alpha} & \text{if} \quad SLQ_i \leq 1 \\ \left[\frac{1}{2}\tanh(SLQ_i - 1) + 1\right]^{\alpha} & \text{if} \quad SLQ_i > 1 \end{cases}$$
$$\mathbf{s}(\beta) = (wx_j^r)^{\beta} \tag{9}$$

One of the main novelties introduced by the 2D-LQ formulation is a modified hyperbolic tangent curve to describe the indirect relationships between input coefficients and location economies.

Papers presenting the 2D-LQ approach (Pereira-López et al., 2020, 2021; Martínez-Alpañez et al., 2023) report better results than previous LQ-based regionalization methods. Such promising results are obtained at the cost of an additional trouble: providing estimates of the α and β parameters that capture the effect of supply-side location economies. Here it is worth examining the pioneering work of Martínez-Alpañez et al. (2023).

The authors use survey-based Korean multiregional IO tables, which arguably should provide a better basis for evaluating the different methods than do the Eurostat data employed in earlier studies, in which selected individual countries are treated as regions of the European Union.

Martínez-Alpañez et al. find that the performance of the 2D-LQ surpasses that of the FLQ for 14 of the 17 regions in the 2015 Korean dataset. The authors also assemble a further dataset comprising survey-based tables for thirteen Spanish regions and find that the 2D-LQ outperforms the FLQ in ten of these regions.

Nevertheless, for the 2D-LQ to be a useful technique in the typical situation where survey-based data are unavailable, it is crucial to be able to obtain reliable estimates of α and β. For Korea, the authors propose the following estimating equations:

$$\hat{\alpha} = 1.66RS + 0.82FET \tag{10}$$

$$\hat{\beta} = 1.64RS + 0.83FIT \tag{11}$$

where *RS* represents regional size measured in terms of gross output, while *FET* and *FIT* measure the weight of interregional and intraregional transport flows, measured in tonnes and divided by the total freight transport flow. *FET* measures the flow destined for other regions, whereas *FIT* measures that from other regions. R^2 = 0.838 for (10) and 0.837 for (11).

Unfortunately, these equations yield highly implausible estimates of α and β. For every region, the values of $\hat{\alpha}$ and $\hat{\beta}$ obtained are almost identical (Martínez-Alpañez et al., 2023, table 5), which suggests that $\alpha = \beta$. That, in turn, would reduce the 2D-LQ method to a single dimension. Clearly, more research needs to be undertaken to develop suitable estimating equations, which would require identification of distinct factors determining the value of each parameter.

1.2 Open debates on curve shapes and parameters

The way we model the indirect relationships between regional size and input coefficients might also be open to discussion. For instance, McCann and Dewhurst (1998) suggested that the FLQ might not be the best way to capture relationships between regional size and interindustry structures. Fig. 1 depicts the relationship between λ, δ and regional size, R, which is measured in terms of a region's share of total national output or employment. The graphs are based on a formulation proposed by Flegg and Webber (1997). A key feature of the graphs is that they pass through the points [0,0] and [1,1]. Furthermore, the gradients decline smoothly and continuously as R increases.

However, the authors offer no rationale for the shape of the graphs in between [0,0] and [1,1], which is an aspect that is worth reconsidering. For instance, in the smallest regions, a relatively small rise in R would result in a large increment in λ. There is no obvious reason why that should be so.

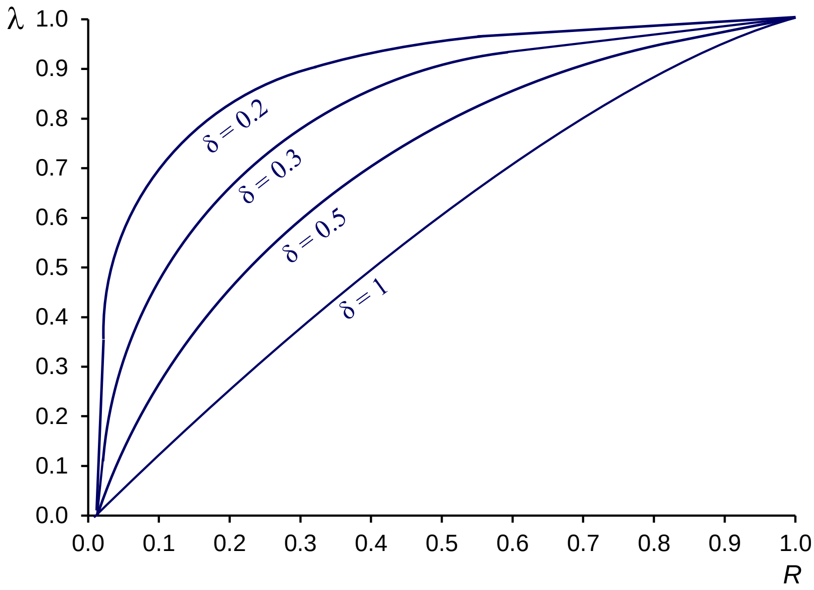


Fig. 1. Convexity for different $\boldsymbol{\delta}$ values in the FLQ formula
Source: own elaboration

Moreover, a critical mass of plants and employment might be required before industrial take-off and clustering dynamics appear within a region. Such dynamics would tend to reduce imports from other regions. The impact of regional heterogeneity should also be considered, especially in the case of relatively large regions in relatively small nations. Here it might be desirable to have some control over how far the estimated regional input coefficients could diverge from their national counterparts as R varies.

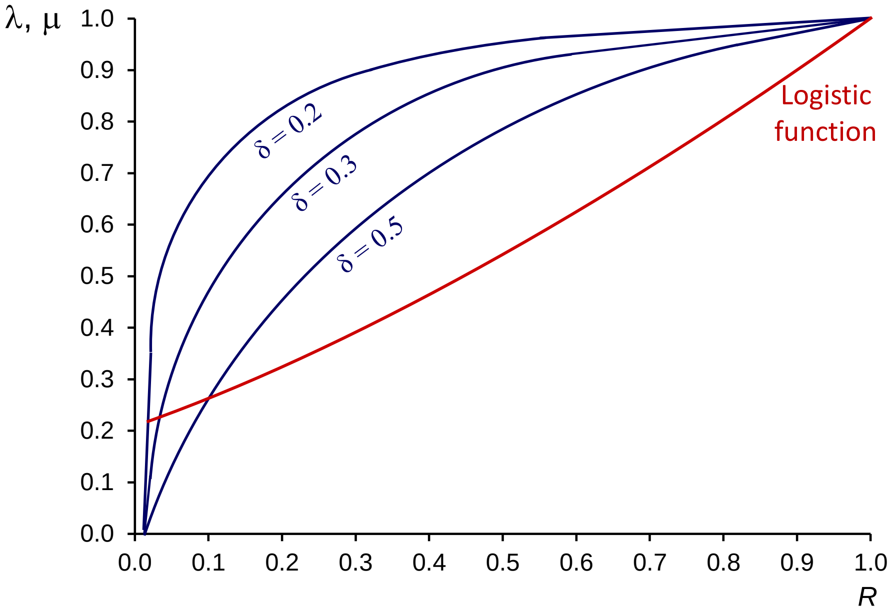


Fig. 2. Example of a logistic function (hyperbolic tangent) versus the FLQ for different $\boldsymbol{\delta}$ values
Source: own elaboration

According to Jarne et al. (2007), S-shaped curves can describe processes characterized by emergent, inflexion and saturation phases. Such phases can be captured in a logistic function, whose general form is as follows:

$$f(x) = \frac{k}{1 + be^{-ax}}, k, a, b \in \Re \tag{12}$$

For our purposes, a special case of this logistic equation, namely the hyperbolic tangent, is the most appropriate. It can be derived by setting $k = 2$, $a = 2$ and $b = 1$, which gives:

$$f(x) = \tanh(x) = \frac{2}{1 + e^{-2x}} \tag{13}$$

Here we use $x - 1$ instead of x, so that:

$$f(x) = \tanh(x - 1) + 1 = \frac{2}{1 + e^{-2(x-1)}} \tag{14}$$

Equation (14) has the following notable properties:

$$\begin{gathered} \lim_{x \to \infty} = \frac{2}{1 + e^{-2(x-1)}} = 2 \\ \lim_{x \to -\infty} \frac{2}{1 + e^{-2(x-1)}} = 0 \end{gathered} \tag{15}$$

Crucially, we have $f(1) = 1$ and $f(0) > 0$.

Figure 2 illustrates the type of logistic function we have in mind. Admittedly, this is one possibility among many. For instance, U-shaped (Duarte et al., 2022; Stöllinger, 2021) and inverted U-shaped curves (Kitsos et al., 2023) are also used to model regional economic dynamics.

Regardless of our choice of curve, the main obstacle in applying the FLQ formula is in determining a value for δ in equation (6). This is crucial because its value might vary across regions, countries and time. This problem can be addressed by applying the FLQ+ approach proposed by Flegg et al. (2021). This approach is discussed next.

The FLQ+ procedure involves three steps. The first applies a modified cross-entropy method to regionalize the national IO table. This is designed to account for negative or zero input coefficients. The second step uses the derived regional matrix, along with the national table, to estimate the optimal δ for each region via a simple regression model. In the third step, this estimated δ is used to apply the FLQ formula, thereby computing the final estimates of the regional input coefficients. These estimates are specific to a particular region, country and time. This hybrid approach can easily be adapted to enhance the performance of other pure LQ-based methods such as the AFLQ that depend on one or more unknown parameters. However, the approach does not encompass the possibility that δ would vary across sectors too (Flegg and Tohmo, 2019; Kowalewksi, 2015; Zhao and Choi, 2015).

1.3 The aim of the present paper

In this paper, we explore an alternative treatment of the indirect relationships between regional attributes (e.g.: regional size) and economic integration across industries. We use a particular form of the logistic function to model such indirect linkages, in the vein of some literature on innovation and technological change. We posit a relationship starting at a non-zero parameter, with a gradient that rises gently as regional supply self-sufficiency increases. Our hypothesis is that, when compared with Figure 1, the logistic curve depicted in Figure 2 can more successfully capture the initial stages, take-off and maturing dynamics of a given industry across both time and space.

We also provide an example of how our method could be implemented without involving parameter estimations. We evaluate if our new method works well with non-parametric rectifications. To this end, we choose a proxy for regional supply self-sufficiency and introduce it directly into our calculations. Moreover, we study the extent to which introducing industry-specific information could improve the accuracy of our estimates.

The remainder of this paper is organized as follows. In section 2, we provide a detailed description of our methodological proposal. We first revise Flegg's original method to introduce an alternative S-shaped hyperbolic tangent treatment in its CILQ part. We next present a non-parametric alternative rectification of the CILQ estimates. Section 3 illustrates our findings, with an empirical application using the Korean 2005 and 2015 IRIO models. In section 4, we perform a sensitivity analysis using different measures of error to assess the robustness of our findings. We conclude with some final remarks.

2 METHODOLOGICAL PROPOSAL

We start by considering a transformation of the CILQ formula using a sigmoidal function (cf. Sánchez-Chóez et al., 2022). Thus, we account for supply/demand relative sizes. Following the FLQ approach, we retain a rectification parameter μ related to a region's degree of supply self-sufficiency but, unlike the CILQ, we prevent excessive rectifications. We call this formula the *reformulated* FLQ or RFLQ, which is specified as follows:

$$RFLQ_{ij} = \mu\left(\tanh\left(CILQ_{ij} - 1\right) + 1\right) \quad (16)$$

In this equation, we still rely on a parameter μ. Our aim is to capture the effect of using an alternatively shaped curve. In doing so, we employ the same hyperbolic tangent modification, as explained in equations (12) to (15) and depicted in Figure 2. Furthermore, we explore if the value of μ can be determined a priori according to available or estimated data. We apply the same smoothing to our proxy data as we do to the CILQ. Thereafter, we employ equation (16).

Now let **Z** stand for a matrix of intermediate flows. Our first non-parametric scenario, NP1, can be formalized as follows:

$$NP1_{ij} = \bar{\mu}^r\left(\tanh\left(CILQ_{ij} - 1\right) + 1\right) \quad (17)$$

where:

$$\bar{\mu}^r = \tanh\left(\frac{z_{\bullet\bullet}^{rr}}{z_{\bullet\bullet}^{\bullet r}} - 1\right) + 1 \quad r \subset n \quad (18)$$

In equation (18), a dot (•) stands for summation across a given dimension: in superscripts, denoting origin or destination; in subscripts, denoting supplying or demanding industries. Therefore, $z_{\bullet\bullet}^{rr}$ stands for intraregionally supplied intermediates and $z_{\bullet\bullet}^{\bullet r}$ for total nationally supplied intermediates (both intraregional and interregional). $\bar{\mu}^r$ denotes our non-parametric estimate of μ for region r. Even though such data might not be available in all countries and regions, literature suggests several ways to estimate these figures. See Thissen et al. (2018) for a recent application to build the EUREGIO dataset.

Finally, we conceive a more information-demanding scenario, NP2, with industry-specific rectifications, as in Zhao and Choi (2015). We proceed as in NP1. Formally:

$$NP2_{ij} = \bar{\mu}_j^r \left(\tanh\left(CILQ_{ij} - 1\right) + 1\right) \tag{19}$$

where:

$$\bar{\mu}^r = \tanh\left(\frac{z_{\bullet j}^{rr}}{z_{\bullet j}^{\bullet r}} - 1\right) + 1 \quad r \subset n \tag{20}$$

In equation (20), $z_{\bullet j}^{rr}$ stands for intraregionally supplied intermediates by industry j and $z_{\bullet j}^{\bullet r}$ for total nationally supplied intermediates by this industry. Because of the amount of data required, this equation only provides an ideal scenario, which we use for counterfactual comparisons.

3 EMPIRICAL APPLICATION

3.1 Methods and data

We now present an empirical application to illustrate our approach. We aggregate the Korean IRIO models for 2005 and 2015 up to 31 sectors. Despite possible biases induced by aggregation (Lahr and Stevens, 2002), that is the only way we could find to establish straightforward comparisons across time. We subsequently aggregate all trade flows into national IO models. Our aim is to extract a regional model for each region from the national matrices using our methodology.

Our detailed results for the two years are presented in Tables 1 and 2, which display the values of the following statistic for each region and method:

$$STPE = 100\ \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\left|\tilde{a}_{ij}^r - a_{ij}^r\right|}{\sum_{i=1}^{n}\sum_{j=1}^{n} a_{ij}^r} \tag{21}$$

where *STPE* is the standardized total percentage error, $\tilde{a}_{ij}^r$ stands for the estimated regional input coefficients and a_{ij}^r for their true counterparts. For the four parametric methods (FLQ, AFLQ, 2D-LQ and RFLQ), we take the parameter value that minimizes the *STPE* for a sequence from 0 to 1, with steps of 0.01.

3.2 Results

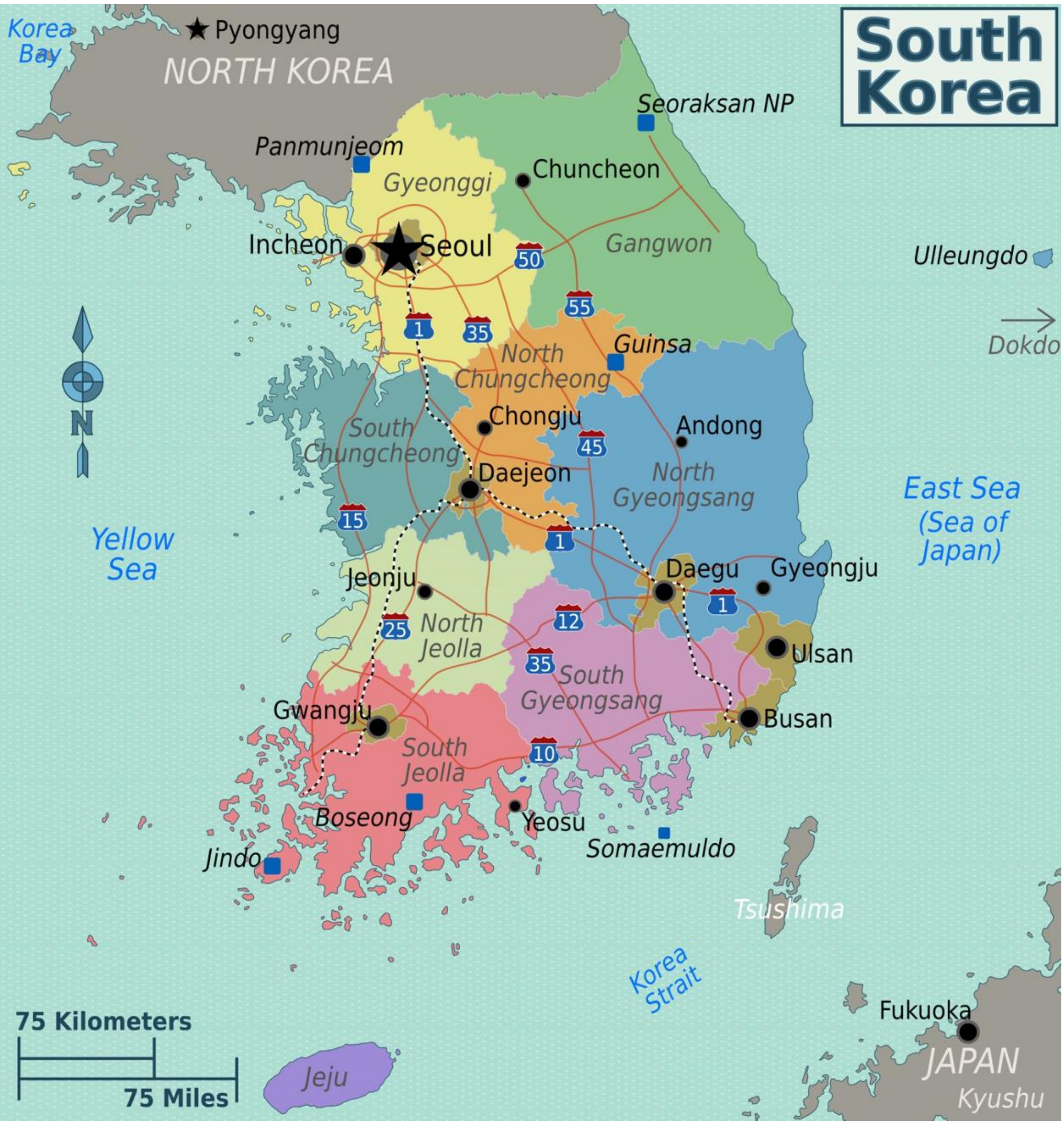
Our full set of detailed results is presented in Tables 1 and 2 but it is helpful to start by considering the rankings of the parametric methods in terms of the *STPE*, which are shown in Tables 3 and 4. A key finding is the excellent performance of the 2D-LQ approach. It gives the best results for 13 of the 16 regions in 2005 and takes second place in the others. This outstanding performance is mirrored in 2015. By contrast, the CILQ is clearly the worst approach in both years. We may note too that the FLQ outperforms the AFLQ in 11 out of 16 cases in 2005 and in 13 out of 17 cases in 2015.

The comparative outcomes for the FLQ and RFLQ are also very interesting. Here the RFLQ gives better results than the FLQ for 13 of the 16 regions in 2005. The only exceptions are Seoul, Busan and Gangwon. The location of these regions is shown in Figure 3. In 2015, the RFLQ outperforms the FLQ in all regions apart from Seoul, where its performance is very poor. Even so, in terms of rankings, it is evident that the RFLQ is a big improvement on the FLQ. What is striking about the outcomes in the two years is the similarity of the rankings, notwithstanding the gap of ten years.

Table 5 provides some useful extra information regarding the parametric methods. One can see that the mean values of α, β and δ are very similar in the two years, while there is a more noticeable difference in the mean values of μ. In terms of dispersion, this is clearly much greater for α than it is for β. It is worth noting here that α and β are the influential parameters in the correction by rows and columns, respectively. It is also evident that α fluctuates substantially more than does δ. Finally, it is interesting that parameter μ for the RFLQ exhibits substantially less dispersion than does δ for the FLQ.

The optimal values of μ, shown in parentheses in Tables 1 and 2, are also worth examining. For the initial year 2005, we can discern a tendency for μ to decline as regions get smaller: for the four largest regions, the mean value of μ is 0.530; for the next seven regions, it is 0.394; while, for the four smallest regions, it is 0.298. By contrast, the values of μ for the year 2015 do not vary so greatly across regions: the mean is 0.553 for the four largest regions, whereas it is 0.464 for the next seven and 0.460 for the five smallest regions. We have ignored the new and very small region of Sejong in this comparison.

Fig. 3. South Korean regions



Source: [South Korea regions map.png] author: Peter Fitzgerald, [NordNordWest]; licensed under the [Creative Commons] Attribution-Share Alike [4.0 International]; available in Wikimedia Commons.

Notwithstanding the impressive results for the 2D-LQ revealed in Tables 1 and 2, there is a potential problem in the application of this method: it involves two unknown parameters, α and β, whose optimal values vary noticeably across regions, especially so in the case of α. However, our results, as reported in Tables 1 and 2, and summarized in Table 5, are at variance with the findings of Pereira-López et al. (2020). Based on an analysis of Eurostat data for six European countries in 2005, they found that the range of suitable values of α and β was relatively small. Furthermore, they suggested that analysts would not go far wrong by choosing an α of 0.1 or 0.15 and a β in the range 0.8 to 1.2. The reasons for these strikingly different findings are hard to explain.

Turning now to the choice between 2D-LQ and RFLQ, a considerable advantage of using the RFLQ rather than the 2D-LQ is that one can avoid the complex task of finding suitable values for α and β. Like the FLQ, the RFLQ has only one unknown parameter μ and it is important to consider how one might obtain a value in a practical application. Here our non-parametric scenario NP1, which is much less information-demanding than the alternative scenario NP2, can be of some assistance.

In fact, Table 2 reveals that the outcomes for NP1 in 2015 very closely match those for the RFLQ, with a negligible difference in the *STPE* in all regions except for the smallest, Sejong. This is a very important finding, as it offers a way of obtaining good estimates of μ for use in the RFLQ method. It should be recalled that the RFLQ results displayed in Table 2 were computed using the optimal values of μ obtained from a full set of survey-based data. Such data would rarely be available in a practical application. Looking now at the outcomes for 2005 in Table 1, it is evident that there is a negligible difference in the outcomes for NP1 and RFLQ in half of the regions. Of the other regions, South Joella and Daejeon stand out as having fairly large differences in the outcomes. There is no obvious reason why NP1 should perform so well in 2015 yet produce rather more mixed results in 2005.

As expected, the NP2 scenario yields a substantially more accurate set of results than does the NP1 scenario. However, the sector-specific data underlying NP2 would not normally be available to analysts and the results are presented merely for illustrative purposes.

Finally, it is worth remarking that our results for the RFLQ and NP1 are very encouraging in the sense that they demonstrate that, with reasonable information requirements, we can gain estimates that are more accurate than those obtainable from the traditional FLQ. What is more, this specification does not rely on any unknown parameter.

4 SENSITIVITY ANALYSIS

In this section, we examine the robustness of our findings by varying the measure of error employed. The following alternatives to the *STPE* (see equation 21) are considered here:

$$MAD = \frac{1}{n^2} \sum_{j=1}^{n} \left| \tilde{a}_{ij}^{r} - a_{ij}^{r} \right| \tag{22}$$

$$MAPE = \frac{100}{n^2} \sum_{i=1}^{n} \sum_{j=1}^{n} \left| \tilde{a}_{ij}^{r} - a_{ij}^{r} \right| \Big/ \sum_{i=1}^{n} \sum_{j=1}^{n} a_{ij}^{r} \tag{23}$$

$$U = 100 \sqrt{\sum_{i=1}^{n} \sum_{j=1}^{n} (a_{ij}^{r} - \tilde{a}_{ij}^{r})^2 \Big/ \sum_{i=1}^{n} \sum_{j=1}^{n} (a_{ij}^{r})^2} \tag{24}$$

where n = 31 is the number of sectors. *MAD* measures the mean absolute deviation of the estimated coefficients from the observed values. As a relative measure, *MAPE* is a refinement of *MAD* that can be employed to compare accuracy across studies. Since *MAPE* equals *STPE* divided by 961, it is simply a matter of convenience which measure is used. *STPE* and *MAPE* would yield identical rankings of techniques, as would *MAD*.

Theil's index *U* is an attractive measure since it considers simultaneously two sources of simulation errors: bias and dispersion. However, a possible demerit is that the use of squared differences has the effect of emphasizing any large positive or negative errors. We should expect *U* to yield similar but not identical rankings of techniques as the other measures.

The results for *STPE*, *MAD* and *MAPE* in 2015 are displayed in Tables 2, 6 and 7. It can be verified that the rankings are unaffected by a change in the error criterion. Moreover, the optimal values of the parameters are unchanged.

As expected, some changes in rankings arise once Theil's criterion *U* is used to assess accuracy. The 2D-LQ is still the best method for 14 out of 17 regions according to all four criteria. However, this overall outcome masks a very minor and offsetting change in the rankings of two regions when Theil's measure is applied. More fundamentally, whereas the *STPE*, *MAD* and *MAPE* judge the RFLQ to be superior to the FLQ in all but one region, Table 8 reveals that this is only true for 9 out of 17 regions according to *U*. Most of the changes in ranking occur in the smallest regions.

It is worth noting, finally, that there is a marked reduction in the size of the optimal values of δ for the FLQ once Theil's criterion is employed. This effect is especially noticeable in the smaller regions and may be a consequence of the squaring of errors, which can exaggerate the weighting of atypically large negative or positive errors.

5 CONCLUDING REMARKS

In this paper, we re-examine how regional size, R, is incorporated in the FLQ formula and simplify the way in which R affects the allowance made for imports from other regions. We call this new formula the *reformulated* FLQ or RFLQ. We find that the use of a hyperbolic tangent formulation yields enhanced results and can be justified theoretically. Using Korean survey-based interregional data, we demonstrate that the RFLQ outperforms the FLQ in 13 of the 16 regions in 2005. In 2015, it does so in all 17 regions apart from Seoul, where its accuracy is very poor. However, once the *STPE* is replaced by Theil's criterion U, the RFLQ outperforms the FLQ in only 9 of these 17 regions. This lack of robustness is a little concerning, although it should be borne in mind that U would tend to exaggerate the importance of any atypically large simulation errors, and this may be the explanation here.

In choosing between the FLQ and RFLQ, it is important to consider their data requirements. For the FLQ, one would need regional sectoral output or employment data, which should not be problematic, whereas obtaining suitable values for the unknown parameter δ would be more challenging. However, such values could be estimated via the FLQ+ method. As noted earlier, these estimates would be specific to a particular region, country and time. By contrast, the RFLQ has an unknown parameter μ, which measures the proportion of intermediate inputs supplied intraregionally. If the required data are not readily available, a proxy would need to be found.

We also consider possible alternatives to the FLQ and RFLQ, especially the 2D-LQ, which gives the best results for 13 of the 16 regions in 2005 and takes second place in the others. This outstanding performance is mirrored in 2015. Nevertheless, such promising results are obtained at the cost of an additional trouble: providing estimates of the unknown parameters α and β. For our datasets, the optimal values of α and β vary noticeably across regions, especially so in the case of α. Therefore, for the 2D-LQ to be a useful addition to the regional analyst's toolkit, it is crucial that suitable estimating equations be developed for α and β.

It is worth noting, finally, that our focus has been on relatively straightforward approaches that can be implemented using readily available data. Of course, more complex approaches, requiring data less readily available, do exist. Such approaches should produce more accurate results but at the cost of additional complexity and more demanding data requirements. A good example is the regression study by Lahr et al. (2020), which is discussed by Flegg et al. (2021). A key issue is whether the regression results obtained from one dataset can be transferred to another context.

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Authors' Contributions

This paper reports the results of a collaborative study by the authors, all of whom have read and approved the final manuscript.

Data Availability

The basic data were downloaded from the Bank of Korea's website, bok.or.kr. For instance, for 2015, the link is:

https://www.bok.or.kr/eng/bbs/E0000634/view.do?nttId=10059403&menuNo=40006&pageIndex=12

Table 1. STPE results for alternative regionalization techniques, year 2005. Source: own elaboration.

	Region (2005)	Regional size (%)	CILQ	FLQ (δ)	AFLQ (δ)	2D-LQ (α; β)	RFLQ (μ)	NP1	NP2
1	Gyeonggi	20.14	69.90	41.56	42.73	37.49	39.16	39.32	35.50
				(0.56)	(0.62)	(0.68; 0.42)	(0.55)		
2	Seoul	18.20	54.36	51.11	57.42	41.80	68.94	68.96	58.07
				(0.19)	(0.71)	(0.72; 0.25)	(0.58)		
3	North Gyeongsang	8.42	82.39	61.06	67.54	53.64	54.43	54.53	49.47
				(0.69)	(0.81)	(0.32; 0.29)	(0.49)		
4	South Gyeongsang	7.35	73.56	55.56	60.53	52.45	51.66	51.67	47.28
				(0.45)	(0.53)	(0.52; 0.30)	(0.50)		
5	Ulsan	7.11	106.77	79.79	83.60	64.28	61.43	64.34	57.01
				(0.56)	(0.89)	(0.16; 0.28)	(0.37)		
6	South Jeolla	6.46	84.98	75.68	75.22	53.80	61.93	69.88	54.24
				(0.38)	(0.95)	(0.40; 0.22)	(0.40)		
7	South Chungcheong	6.33	112.65	69.24	66.41	53.05	53.14	55.41	49.80
				(0.64)	(0.67)	(0.16; 0.32)	(0.39)		
8	Incheon	5.49	116.02	57.61	58.69	50.30	46.68	48.00	46.02
				(0.54)	(0.70)	(0.32; 0.36)	(0.40)		
9	Busan	5.06	85.35	52.99	52.59	49.70	54.66	55.32	49.07
				(0.40)	(0.44)	(1.04; 0.23)	(0.42)		
10	North Chungcheong	2.92	100.61	68.98	70.35	61.99	62.13	63.06	56.39
				(0.50)	(0.52)	(0.40; 0.32)	(0.36)		
11	Daegu	2.88	84.62	57.78	58.34	50.50	55.23	55.45	49.96
				(0.30)	(0.34)	(0.88; 0.25)	(0.42)		
12	North Jeolla	2.74	107.54	69.88	70.15	58.24	62.49	65.41	58.57
				(0.46)	(0.54)	(0.52; 0.29)	(0.32)		
13	Gangwon	2.16	97.97	71.99	72.15	58.16	73.62	76.23	67.83
				(0.18)	(0.33)	(0.64; 0.15)	(0.38)		
14	Gwangju	2.15	112.48	72.81	72.55	60.65	65.47	68.35	61.63
				(0.37)	(0.44)	(0.64; 0.28)	(0.30)		
15	Daejeon	1.93	152.24	87.61	87.27	74.61	74.96	86.06	76.18
				(0.67)	(0.75)	(0.84; 0.36)	(0.19)		
16	Jeju	0.67	94.19	83.92	86.23	53.10	79.24	84.20	72.86
				(0.20)	(0.33)	(0.96; 0.13)	(0.30)		

Table 2. STPE results for alternative regionalization techniques, year 2015. Source: own elaboration.

	Region (2015)	Regional size (%)	CILQ	FLQ ($\boldsymbol{\delta}$)	AFLQ ($\boldsymbol{\delta}$)	2D-LQ ($\boldsymbol{\alpha}$; $\boldsymbol{\beta}$)	RFLQ ($\boldsymbol{\mu}$)	NP1	NP2
1	Gyeonggi	22.85	61.53	39.41	40.44	34.23	33.25	33.28	31.04
				(0.55)	(0.58)	(0.44; 0.42)	(0.55)		
2	Seoul	18.97	56.93	56.59	61.66	41.99	70.25	70.37	60.95
				(0.16)	(0.58)	(0.76; 0.17)	(0.62)		
3	North Gyeongsang	7.00	76.31	55.67	61.52	44.65	45.46	45.57	41.89
				(0.35)	(0.41)	(0.28; 0.29)	(0.48)		
4	South Gyeongsang	6.93	67.13	55.82	63.74	46.83	45.19	45.61	41.59
				(0.27)	(0.52)	(0.36; 0.23)	(0.56)		
5	Ulsan	6.32	99.33	73.55	75.35	56.51	52.68	53.37	49.67
				(0.65)	(0.73)	(0.04; 0.30)	(0.43)		
6	South Jeolla	4.89	75.21	65.82	72.03	46.69	54.22	55.16	46.53
				(0.29)	(0.30)	(0.52; 0.19)	(0.49)		
7	South Chungcheong	6.96	94.44	67.93	68.15	58.66	57.42	58.58	53.88
				(0.64)	(0.69)	(0.08; 0.37)	(0.41)		
8	Incheon	4.96	100.01	51.33	52.64	48.56	49.46	49.74	46.41
				(0.48)	(0.55)	(0.80; 0.26)	(0.42)		
9	Busan	4.73	68.68	49.95	49.93	42.74	46.64	47.37	41.78
				(0.28)	(0.33)	(0.92; 0.20)	(0.58)		
10	North Chungcheong	3.47	100.86	72.38	73.68	62.01	64.18	64.39	58.28
				(0.48)	(0.62)	(0.12; 0.34)	(0.41)		
11	Daegu	2.82	77.21	58.77	58.16	44.53	51.39	51.71	46.50
				(0.29)	(0.31)	(1.04; 0.19)	(0.51)		
12	North Jeolla	2.82	82.42	62.71	64.11	50.30	55.35	55.35	49.04
				(0.33)	(0.33)	(0.64; 0.19)	(0.49)		
13	Gangwon	1.97	88.31	67.63	64.74	52.46	67.15	67.17	59.90
				(0.40)	(0.42)	(0.88; 0.19)	(0.46)		
14	Gwangju	2.07	91.12	69.87	72.12	52.27	59.53	59.56	53.60
				(0.35)	(0.41)	(1.08; 0.18)	(0.46)		
15	Daejeon	1.92	124.34	79.82	78.86	59.84	64.35	64.38	58.37
				(0.44)	(0.47)	(1.04; 0.25)	(0.41)		
16	Jeju	0.81	77.16	71.21	71.37	48.13	69.39	69.39	60.85
				(0.19)	(0.27)	(0.68; 0.13)	(0.48)		
17	Sejong	0.50	183.03	87.88	88.30	72.63	76.65	87.41	78.75
				(0.59)	(0.60)	(0.60; 0.29)	(0.19)		

Table 3. Ranking of alternative parametric regionalization techniques: year 2005, STPE. Source: table 1.

	Region (2005)	Regional size (%)	CILQ	FLQ	AFLQ	2D-LQ	RFLQ
1	Gyeonggi	20.14	5	3	4	**1**	2
2	Seoul	18.20	3	2	4	**1**	5
3	North Gyeongsang	8.42	5	3	4	**1**	2
4	South Gyeongsang	7.35	5	3	4	2	**1**
5	Ulsan	7.11	5	3	4	2	**1**
6	South Jeolla	6.46	5	4	3	**1**	2
7	South Chungcheong	6.33	5	4	3	**1**	2
8	Incheon	5.49	5	3	4	2	**1**
9	Busan	5.06	5	3	2	**1**	4
10	North Chungcheong	2.92	5	3	4	**1**	2
11	Daegu	2.88	5	3	4	**1**	2
12	North Jeolla	2.74	5	3	4	**1**	2
13	Gangwon	2.16	5	2	3	**1**	4
14	Gwangju	2.15	5	4	3	**1**	2
15	Daejeon	1.93	5	4	3	**1**	2
16	Jeju	0.67	5	3	4	**1**	2

Table 4. Ranking of alternative parametric regionalization techniques: year 2015, STPE. Source: table 2.

	Region (2015)	**Regional size (%)**	**CILQ**	**FLQ**	**AFLQ**	**2D-LQ**	**RFLQ**
1	Gyeonggi	22.85	5	3	4	2	**1**
2	Seoul	18.97	3	2	4	**1**	5
3	North Gyeongsang	7.00	5	3	4	**1**	2
4	South Gyeongsang	6.93	5	3	4	2	**1**
5	Ulsan	6.32	5	3	4	2	**1**
6	South Jeolla	4.89	5	3	4	**1**	2
7	South Chungcheong	6.96	5	3	4	2	**1**
8	Incheon	4.96	5	3	4	**1**	2
9	Busan	4.73	5	4	3	**1**	2
10	North Chungcheong	3.47	5	3	4	**1**	2
11	Daegu	2.82	5	4	3	**1**	2
12	North Jeolla	2.82	5	3	4	**1**	2
13	Gangwon	1.97	5	4	2	**1**	3
14	Gwangju	2.07	5	3	4	**1**	2
15	Daejeon	1.92	5	4	3	**1**	2
16	Jeju	0.81	5	3	4	**1**	2
17	Sejong	0.50	5	3	4	**1**	2

Table 5. Means and coefficients of variation of parameters

Formula	FLQ	2D-LQ		RFLQ
Parameter	δ	α	β	μ
Mean 2005	0.44	0.58	0.28	0.40
Mean 2015	0.40	0.60	0.25	0.47
V (%) 2005	38	47	27	25
V (%) 2015	38	57	32	20

Note: V = coefficient of variation. Source: own elaboration.

Table 6. MAPE results for alternative regionalization techniques, year 2015. Source: own elaboration.

	Region (2015)	Regional size (%)	CILQ	FLQ (δ)	AFLQ (δ)	2D-LQ (α; β)	RFLQ (μ)	NP1	NP2
1	Gyeonggi	22.85	0.06403	0.04101	0.04208	0.03561	0.03460	0.03463	0.03230
				(0.55)	(0.58)	(0.44; 0.42)	(0.55)		
2	Seoul	18.97	0.05924	0.05889	0.06416	0.04369	0.07310	0.07322	0.06343
				(0.16)	(0.58)	(0.76; 0.17)	(0.62)		
3	North Gyeongsang	7.00	0.07940	0.05793	0.06402	0.04646	0.04731	0.04742	0.04359
				(0.35)	(0.41)	(0.28; 0.29)	(0.48)		
4	South Gyeongsang	6.93	0.06986	0.05809	0.06632	0.04873	0.0341	0.04746	0.04328
				(0.27)	(0.52)	(0.36; 0.23)	(0.56)		
5	Ulsan	6.32	0.10336	0.07653	0.07855	0.05880	0.05482	0.05553	0.05169
				(0.65)	(0.73)	(0.04; 0.30)	(0.43)		
6	South Jeolla	4.89	0.07826	0.06849	0.07495	0.04859	0.05642	0.05740	0.04842
				(0.29)	(0.30)	(0.52; 0.19)	(0.49)		
7	South Chungcheong	6.96	0.09828	0.07069	0.07092	0.06104	0.05975	0.06096	0.05606
				(0.64)	(0.69)	(0.08; 0.37)	(0.41)		
8	Incheon	4.96	0.10407	0.05341	0.05477	0.05053	0.05147	0.05176	0.04829
				(0.48)	(0.55)	(0.80; 0.26)	(0.42)		
9	Busan	4.73	0.07147	0.05198	0.05195	0.04448	0.04853	0.04929	0.04348
				(0.28)	(0.33)	(0.92; 0.20)	(0.58)		
10	North Chungcheong	3.47	0.10496	0.07532	0.07667	0.06453	0.06678	0.06700	0.06064
				(0.48)	(0.62)	(0.12; 0.34)	(0.41)		
11	Daegu	2.82	0.08035	0.06115	0.06052	0.04633	0.05347	0.05381	0.04839
				(0.29)	(0.31)	(1.00; 0.19)	(0.51)		
12	North Jeolla	2.82	0.08577	0.06526	0.06671	0.05234	0.05760	0.05760	0.05103
				(0.33)	(0.33)	(0.64; 0.19)	(0.49)		
13	Gangwon	1.97	0.09189	0.07037	0.06737	0.05469	0.06988	0.06989	0.06234
				(0.40)	(0.42)	(0.88; 0.19)	(0.46)		
14	Gwangju	2.07	0.09482	0.07270	0.07505	0.05439	0.06195	0.06198	0.05578
				(0.35)	(0.41)	(1.08; 0.18)	(0.46)		
15	Daejeon	1.92	0.12939	0.08305	0.08206	0.06227	0.06696	0.06699	0.06074
				(0.44)	(0.47)	(1.04; 0.25)	(0.41)		
16	Jeju	0.81	0.08029	0.07410	0.07427	0.05009	0.07221	0.07221	0.06332
				(0.19)	(0.27)	(0.68; 0.13)	(0.48)		
17	Sejong	0.50	0.19046	0.09145	0.09188	0.07557	0.07976	0.09096	0.08195
				(0.59)	(0.60)	(0.60; 0.29)	(0.19)		

Table 7. MAD results for alternative regionalization techniques, year 2015. Source: own elaboration.

	Region (2015)	**Regional size (%)**	**CILQ**	**FLQ ($\boldsymbol{\delta}$)**	**AFLQ ($\boldsymbol{\delta}$)**	**2D-LQ ($\boldsymbol{\alpha}$; $\boldsymbol{\beta}$)**	**RFLQ ($\boldsymbol{\mu}$)**	**NP1**	**NP2**
1	Gyeonggi	22.85	0.00502	0.00321	0.00330	0.00279	0.00271	0.00271	0.00253
				(0.55)	(0.58)	(0.44; 0.42)	(0.55)		
2	Seoul	18.97	0.00386	0.00384	0.00418	0.00285	0.00476	0.00477	0.00413
				(0.16)	(0.58)	(0.76; 0.17)	(0.62)		
3	North Gyeongsang	7.00	0.00550	0.00401	0.00443	0.00322	0.00327	0.00328	0.00302
				(0.35)	(0.41)	(0.28; 0.29)	(0.48)		
4	South Gyeongsang	6.93	0.00506	0.00421	0.00480	0.00353	0.00341	0.00344	0.00313
				(0.27)	(0.52)	(0.36; 0.23)	(0.56)		
5	Ulsan	6.32	0.00656	0.00486	0.00498	0.00373	0.00348	0.00352	0.00328
				(0.65)	(0.73)	(0.04; 0.30)	(0.43)		
6	South Jeolla	4.89	0.00529	0.00463	0.00507	0.00328	0.00381	0.00388	0.00327
				(0.29)	(0.30)	(0.52; 0.19)	(0.49)		
7	South Chungcheong	6.96	0.00667	0.00481	0.00481	0.00414	0.00406	0.00414	0.00381
				(0.64)	(0.69)	(0.08; 0.37)	(0.41)		
8	Incheon	4.96	0.00638	0.00327	0.00336	0.00310	0.00315	0.00317	0.00296
				(0.48)	(0.55)	(0.80; 0.26)	(0.42)		
9	Busan	4.73	0.00515	0.00375	0.00375	0.00321	0.00350	0.00355	0.00314
				(0.28)	(0.33)	(0.92; 0.20)	(0.58)		
10	North Chungcheong	3.47	0.00626	0.00449	0.00457	0.00385	0.00398	0.00400	0.00362
				(0.48)	(0.62)	(0.12; 0.34)	(0.41)		
11	Daegu	2.82	0.00529	0.00403	0.00398	0.00305	0.00352	0.00354	0.00319
				(0.29)	(0.31)	(1.00; 0.19)	(0.51)		
12	North Jeolla	2.82	0.00562	0.00427	0.00437	0.00343	0.00377	0.00377	0.00334
				(0.33)	(0.33)	(0.64; 0.19)	(0.49)		
13	Gangwon	1.97	0.00570	0.00436	0.00418	0.00338	0.00433	0.00433	0.00387
				(0.40)	(0.42)	(0.88; 0.19)	(0.46)		
14	Gwangju	2.07	0.00568	0.00436	0.00450	0.00326	0.00371	0.00371	0.00334
				(0.35)	(0.41)	(1.08; 0.18)	(0.46)		
15	Daejeon	1.92	0.00683	0.00439	0.00433	0.00329	0.00354	0.00354	0.00321
				(0.44)	(0.47)	(1.04; 0.25)	(0.41)		
16	Jeju	0.81	0.00452	0.00417	0.00418	0.00282	0.00407	0.00407	0.00357
				(0.19)	(0.27)	(0.68; 0.13)	(0.48)		
17	Sejong	0.50	0.00737	0.00354	0.00356	0.00293	0.00309	0.00352	0.00317
				(0.59)	(0.60)	(0.60; 0.29)	(0.19)		

Table 8. Theil's *U* results for alternative regionalization techniques, year 2015. Source: own elaboration.

	Region (2015)	Regional size (%)	CILQ	FLQ ($\boldsymbol{\delta}$)	AFLQ ($\boldsymbol{\delta}$)	2D-LQ ($\boldsymbol{\alpha}$; $\boldsymbol{\beta}$)	RFLQ ($\boldsymbol{\mu}$)	NP1	NP2
1	Gyeonggi	22.85	49.30	45.20	53.46	41.28	41.79	46.78	30.91
				(0.26)	(0.42)	(0.40; 0.25)	(0.71)		
2	Seoul	18.97	48.56	48.27	68.97	38.00	65.04	65.30	46.64
				(0.05)	(0.22)	(0.56; 0.11)	(0.54)		
3	North Gyeongsang	7.00	57.59	49.85	73.83	48.42	44.95	48.86	31.35
				(0.21)	(0.62)	(0.20; 0.16)	(0.65)		
4	South Gyeongsang	6.93	57.34	50.50	77.46	51.09	46.35	50.16	32.34
				(0.17)	(0.64)	(0.20; 0.17)	(0.66)		
5	Ulsan	6.32	90.85	80.01	84.50	66.54	65.94	65.96	59.06
				(0.63)	(0.96)	(-0.08; 0.27)	(0.49)		
6	South Jeolla	4.89	47.24	45.32	63.28	42.96	54.55	56.27	37.61
				(0.07)	(0.09)	(0.64; 0.11)	(0.68)		
7	South Chungcheong	6.96	72.82	59.78	64.97	54.55	53.17	55.62	43.28
				(0.38)	(0.47)	(0.08; 0.20)	(0.60)		
8	Incheon	4.96	78.87	60.03	68.03	54.00	54.72	56.22	37.96
				(0.28)	(0.34)	(0.40; 0.20)	(0.54)		
9	Busan	4.73	59.62	49.19	53.42	45.73	50.73	52.41	35.86
				(0.19)	(0.24)	(1.00; 0.14)	(0.61)		
10	North Chungcheong	3.47	73.44	63.66	70.11	56.99	58.81	61.00	43.99
				(0.39)	(0.52)	(0.48; 0.19)	(0.56)		
11	Daegu	2.82	52.96	49.80	60.88	46.30	53.82	58.43	36.96
				(0.05)	(0.17)	(1.04; 0.11)	(0.65)		
12	North Jeolla	2.82	64.71	57.09	62.58	47.84	51.79	55.42	36.83
				(0.24)	(0.33)	(0.68; 0.16)	(0.63)		
13	Gangwon	1.97	56.55	52.56	54.87	46.98	66.56	69.75	48.93
				(0.08)	(0.23)	(1.08; 0.13)	(0.65)		
14	Gwangju	2.07	60.87	55.51	77.90	54.67	57.65	60.55	38.28
				(0.08)	(0.11)	(0.68; 0.11)	(0.59)		
15	Daejeon	1.92	74.79	71.72	76.18	59.11	63.02	65.95	42.35
				(0.08)	(0.30)	(0.88; 0.16)	(0.56)		
16	Jeju	0.81	46.57	44.29	49.10	41.34	61.92	64.00	41.60
				(0.06)	(0.13)	(1.68; 0.14)	(0.60)		
17	Sejong	0.50	71.43	70.40	84.84	53.14	70.95	77.63	44.49
				(0.02)	(0.14)	(1.68; 0.14)	(0.61)		