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FULL ARTICLE

The regionalization of national input-output tables: A study of South Korean regions

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Abstract

This paper uses survey-based data for 16 South Korean regions to refine the application of Flegg's location quotient (FLQ) and its variant, the sector-specific FLQ (SFLQ). These regions vary markedly in terms of size. Especial attention is paid to the problem of choosing appropriate values for the unknown parameter δ in these formulae. Alternative approaches to this problem are evaluated and tested. Our paper adds to earlier research that aims to find a cost-effective way of adapting national coefficients, so as to produce a satisfactory initial set of regional input coefficients for regions where survey-based data are unavailable.

KEYWORDS

input–output, FLQ, location quotients, SFLQ, South Korea

1 | INTRODUCTION

Regional input–output tables contain much useful information to guide regional planners, yet regional tables based largely on survey data are rare. This rarity reflects the expense and difficulty of constructing such tables. Consequently, analysts typically rely on indirect methods of constructing regional tables, by adapting national data using formulae based on location quotients (LQs). However, the paucity of survey-based regional tables makes it very challenging to perform reliable tests of the available non-survey methods. Indeed, most empirical studies of LQ-based methods have examined data for single regions; recent examples include a study of the German state of Baden-Wuerttemberg by Kowalewski (2015) and one of the Argentinian province of Córdoba by Flegg, Mastronardi, and Romero (2016). A potential weakness of such studies is, of course, that they may reflect the idiosyncrasies of particular regions and thus lack generality.

An innovative way of obtaining more general results was proposed by Bonfiglio and Chelli (2008), who employed Monte Carlo methods to generate, for each of 20 regions, 1,000 multiregional tables with 20 sectors, which were aggregated to produce corresponding national tables. They were then able to assess the relative accuracy of several alternative non-survey methods in terms of their ability to estimate the values of 400,000 regional output multipliers. The results demonstrated that Flegg's LQ (FLQ) and its variant, the augmented FLQ (AFLQ), gave by far the best estimates of these multipliers.

Nevertheless, Flegg et al. (2016, p. 33) remark that "the simplifying assumptions underlying a Monte Carlo simulation mean that it cannot replicate the detailed economic structure and sectoral interrelationships of regional economies." This feature may well explain why the results exhibit unusually large mean relative absolute errors (Bonfiglio & Chelli, 2008).

Here we pursue an alternative approach, in an effort to circumvent the limitations of both Monte Carlo methods and single-region studies. To attain greater generality, we examine survey-based tables for 16 South Korean regions of differing size. The reliability of our study is enhanced by the fact that the detailed regional and national tables for the year 2005 were constructed on a consistent basis by the Bank of Korea. Our main aim is to make full use of this valuable data set to refine the application of the FLQ formula for estimating regional input coefficients and hence sectoral output multipliers. We pay especial attention to the choice of a value for the unknown parameter δ in this formula. Along with regional size, this value determines the size of the adjustment for regional imports in the FLQ formula.

Earlier work on this topic using data for two South Korean regions was carried out by Zhao and Choi (2015). However, we argue that there are several key shortcomings in this pioneering study, so an effort is made to address these limitations. In the next section, we discuss the FLQ formula and some related formulae based on LQs. Relevant empirical evidence is also considered. In Section 3, we examine some of Zhao and Choi's key findings but find that they cannot be replicated. We also raise some fundamental methodological issues concerning their approach. In Section 4, we examine the proposed sector-specific FLQ (SFLQ) approach of Kowalewski (2015) and consider how it might be used in a practical context. The penultimate section extends our analysis from two to 16 regions, while the final section concludes.

2 | THE FLQ AND RELATED FORMULAE

LQs offer a simple and cheap way of regionalizing a national input–output table.[1] Earlier analysts have often used the simple LQ (SLQ) or the cross-industry LQ (CILQ), yet both are known to underestimate regional trade. This effect occurs largely because they either rule out (as with the SLQ) or greatly understate (as with the CILQ) the extent of cross-hauling (the simultaneous importing and exporting of a given commodity).[2] The SLQ is defined here as:

$$SLQ_i \equiv \frac{Q_i^r / \sum_i Q_i^r}{Q_i^n / \sum_i Q_i^n} \equiv \frac{Q_i^r}{Q_i^n} \times \frac{\sum_i Q_i^n}{\sum_i Q_i^r}, \tag{1}$$

where Q_i^r is regional output in sector i and Q_i^n is the corresponding national figure. $\Sigma_i Q_i^r$ and $\Sigma_i Q_i^n$ are the respective regional and national totals. Likewise, the CILQ is defined as:

$$CILQ_{ij} \equiv \frac{SLQ_i}{SLQ_j} \equiv \frac{Q_i^r / Q_i^n}{Q_j^r / Q_j^n}, \tag{2}$$

where the subscripts i and j refer to the supplying and purchasing sectors, respectively.

It should be noted that the SLQ and CILQ are defined in terms of output rather than the more usual employment. Using output is preferable to using a proxy such as employment because output figures are not distorted by differences in productivity across regions. Fortunately, regional sectoral output data were readily available in this instance.

[1]See Klijs et al. (2016) for a comparison of LQ-based methods and Morrissey (2016) for an interesting application.

[2]See Flegg and Tohmo (2013b, p. 239 and note 3).

The first step in the application of LQs is to transform the national transactions matrix into a matrix of input coefficients. This matrix can then be 'regionalized' via the formula:

$$r_{ij} = \beta_{ij} \times a_{ij}, \tag{3}$$

where r_{ij} is the regional input coefficient, β_{ij} is an adjustment coefficient and a_{ij} is the national input coefficient (Flegg & Tohmo, 2016). r_{ij} measures the amount of regional input i required to yield one unit of regional gross output j; it thus excludes any supplies of i from other domestic regions or from abroad. Similarly, a_{ij} excludes any foreign inputs. The role of β_{ij} is to take account of a region's purchases of input i from other domestic regions.

We can estimate the r_{ij} by replacing β_{ij} in Equation 3 with an LQ. Thus, for instance:

$$\widehat{r}_{ij} = CILQ_{ij} \times a_{ij}. \tag{4}$$

No scaling is applied to a_{ij} where $CILQ_{ij} \geq 1$ and likewise for SLQ_i. For $i = j$, it is normal to substitute SLQ_i for $CILQ_{ij}$.

The CILQ has the merit that a different scaling can be applied to each cell in a given row of the national coefficient matrix. Unlike the SLQ, the CILQ does not presume that a purchasing sector is either an exporter or an importer of a given commodity but never both. Even so, empirical evidence indicates that the CILQ still substantially understates regional trade. Flegg, Webber, and Elliott (1995) attempted to address this demerit of the CILQ via their FLQ formula, which was later refined by Flegg and Webber (1997). Following Flegg et al. (2016), the FLQ is defined here as:

$$FLQ_{ij} \equiv CILQ_{ij} \times \lambda^*, \text{ for } i \neq j, \tag{5}$$

$$FLQ_{ij} \equiv SLQ_i \times \lambda^*, \text{ for } i = j. \tag{6}$$

Where[3]:

$$\lambda^* \equiv \left[\log_2\left(1 + \textstyle\sum_i Q_i^r / \sum_i Q_i^n\right)\right]^{\delta}. \tag{7}$$

Flegg et al. assume that $0 \leq \delta < 1$; as δ rises, so too does the allowance for interregional imports. $\delta = 0$ is a special case where $FLQ_{ij} = CILQ_{ij}$ for $i \neq j$ and $FLQ_{ij} = SLQ_i$ for $i = j$. As with other LQ-based formulae, the restriction $FLQ_{ij} \leq 1$ is imposed.

Flegg et al. (2016) emphasize two aspects of the FLQ formula: its cross-industry foundations and the explicit role given to regional size. With the FLQ, the relative size of the regional purchasing and supplying sectors is considered when making an adjustment for interregional trade. Furthermore, by taking explicit account of a region's relative size, Flegg and Tohmo (2016) argue that the FLQ should help to address the problem of cross-hauling, which is likely to be more acute in smaller regions than in larger ones. Smaller regions are apt to be more open to interregional trade.

It is now well established that the FLQ can give more precise results than the SLQ and CILQ. This evidence includes, for instance, case studies of Scotland (Flegg & Webber, 2000), Finland (Flegg & Tohmo, 2013a, 2016; Tohmo, 2004), Germany (Kowalewski, 2015), Argentina (Flegg et al., 2016) and Ireland (Morrissey, 2016). This testimony from case studies is bolstered by the Monte Carlo simulation results of Bonfiglio and Chelli (2008) mentioned earlier. Nonetheless, some evidence to the contrary is presented by Lamonica and Chelli (2017), who find initially that the SLQ gives slightly better results than the FLQ.

Lamonica and Chelli's study is unusual since it is based on the World Input–Output Database. The sample comprised 27 European countries, 13 other major countries plus the rest of the world as a composite 'country'. Data for 35 industries (economic sectors) in the period 1995–2011 were examined. However, when the authors

[3]Cf. Flegg and Webber (1997, p. 798), who define λ^* in terms of employment. This reflects the fact that, in most cases, employment has to be used as a proxy for output.

disaggregated their sample into small and large countries, rather different findings emerged. For the smaller economies, characterized by a high percentage of input coefficients close to zero, the FLQ (with δ = 0.2) was the best method, whereas the SLQ performed the best in the larger economies.

The FLQ's focus is on the output and employment generated within a specific region. As Flegg and Tohmo (2013b) point out, it should only be used in conjunction with national input–output tables where the inter-industry transactions exclude imports (type B tables). By contrast, where the focus is on the overall supply of goods, Kronenberg's cross-hauling adjusted regionalization method (CHARM) can be employed (Flegg, Huang, & Tohmo, 2015; Többen & Kronenberg, 2015). CHARM requires type A tables, those where imports have been incorporated into the national transactions table (Kronenberg, 2009, 2012).[4]

A variant of the FLQ is the augmented FLQ (AFLQ) formula devised by Flegg and Webber (2000), which aims to capture the impact of regional specialization on the size of regional input coefficients. This effect is measured via SLQ_j. The AFLQ is defined as:

$$AFLQ_{ij} \equiv FLQ_{ij} \times \log_2(1 + SLQ_j). \tag{8}$$

The specialization term, $\log_2(1 + SLQ_j)$, only applies where $SLQ_j > 1$ (Flegg & Webber, 2000). The AFLQ has the novel property that it can encompass cases where $r_{ij} > a_{ij}$ in Equation 3. As with the FLQ, the constraint $AFLQ_{ij} \leq 1$ is imposed.

Although the AFLQ has some theoretical merits relative to the FLQ, its empirical performance is typically very similar. For instance, in the Monte Carlo study by Bonfiglio and Chelli (2008), the AFLQ gave only slightly more accurate results than the FLQ.[5] This outcome was confirmed by Flegg et al. (2016). Kowalewski (2015) also tested both formulae but again obtained comparable results. For this reason, along with limitations of space, only the FLQ will be examined here.

Another variant of the FLQ is proposed by Kowalewski (2015). Her innovative approach involves relaxing the assumption that δ is invariant across sectors. Kowalewski's industry-specific FLQ, the SFLQ, is defined as:

$$SFLQ_{ij} \equiv CILQ_{ij} \times [\log_2(1 + E^r/E^n)]^{\delta j}, \tag{9}$$

where E^r/E^n is regional size measured in terms of employment. For $i = j$, $CILQ_{ij}$ is replaced by SLQ_i. In order to estimate the values of δ_j, Kowalewski specifies a regression model of the following form:

$$\delta_j = a + \beta_1 CL_j + \beta_2 SLQ_j + \beta_3 IM_j + \beta_4 VA_j + \varepsilon_j, \tag{10}$$

where CL_j is the coefficient of localization, which measures the degree of concentration of national industry j, IM_j is the share of foreign imports in total national intermediate inputs, VA_j is the share of value added in total national output and ε_j is an error term. Regional data are needed for SLQ_j, whereas CL_j, IM_j and VA_j require national data. CL_j is calculated as:

$$CL_j \equiv 0.5 \sum_r \left| \frac{E_j^r}{E_j^n} - \frac{E^r}{E^n} \right|. \tag{11}$$

3 | ZHAO AND CHOI'S STUDY

Zhao and Choi (2015) based their analysis on a 28 × 28 national technological coefficient matrix for 2005 produced by the Bank of Korea. It should be noted that this was a type A matrix, which incorporated imports from abroad.

[4]For a detailed discussion of these two approaches, see Flegg and Tohmo (2018).

[5]See Bonfiglio and Chelli (2008, table 1).

TABLE 1 Estimating output multipliers for two South Korean regions in 2005: Zhao and Choi's findings (MAPE based on 28 sectors)

	Region	
Formula	**Daegu**	**Gyeongbuk**
SLQ	50.78	70.91
CILQ	63.01	61.85
FLQ (δ = 0.3)	14.14	22.89
FLQ (δ = 0.4)	9.36	15.84
FLQ (δ = 0.5)	**8.65**	12.20
FLQ (δ = 0.6)	9.91	**8.48**
Optimal δ	0.5	0.6

Note: Optimal values are shown in bold type.

Source: Zhao and Choi (2015, tables 8 and 9).

Nevertheless, the authors regionalized this matrix by applying various LQ-based formulae calculated using employment data. The Bank divided the country into 16 regions and computed type I output multipliers for each region. Zhao and Choi chose to study two regions in detail, namely Daegu and Gyeongbuk, and used the Bank's regional multipliers as a benchmark for assessing the accuracy of their simulations. As criteria, they used the mean absolute distance and the mean absolute percentage error (MAPE). However, the results from these two measures hardly differed, so only MAPE will be considered here. It was calculated via the formula:

$$\text{MAPE} = (100/n)\sum_j \left|\widehat{m}_j - m_j\right|/m_j, \tag{12}$$

where m_j is the type I output multiplier for sector j and n = 28 is the number of sectors.

A selection of Zhao and Choi's results is presented in Table 1. As expected, the FLQ outperforms the SLQ and CILQ but the extent of this superior performance is striking. It echoes the clear-cut findings in the Monte Carlo study of Bonfiglio and Chelli (2008), yet other authors such as Flegg and Tohmo (2013a, 2016), Flegg et al. (2016) and Kowalewski (2015) have found more modest differences in performance. An interesting facet of the results is that MAPE is minimized at a relatively high value of δ in both regions. However, most other studies, including those mentioned above, have found much lower optimal values.

At the outset, we attempted to replicate Zhao and Choi's results using identical assumptions. To attain greater precision, we used steps of 0.05 for δ. Our findings, which are displayed in Table 2, are clearly somewhat different from theirs. Having checked our own calculations carefully, it is evident that errors of an unknown nature must have occurred in Zhao and Choi's simulations.[6] In the case of Daegu, there is a cut in the optimal δ from 0.5 to 0.4, along with a rise in the corresponding value of MAPE from 8.7% to 9.2%. By contrast, for Gyeongbuk, the optimal δ is still 0.6, yet MAPE has risen sharply from 8.5% to 10.5%. The performance of the SLQ and CILQ is somewhat better in both regions, albeit more so in Daegu than in Gyeongbuk.

A demerit of Zhao and Choi's approach is their use of a type A national coefficient matrix, which would tend to overstate the optimal values of δ. The explanation is straightforward: instead of using the equation $\widehat{r}_{ij} = FLQ_{ij} \times a_{ij}$ to estimate the input coefficients, one would be using the equation $\widehat{r}_{ij} = FLQ_{ij} \times (a_{ij} + f_{ij})$, where f_{ij} is the national propensity to import from abroad. Minimizing MAPE would then require a higher δ.

Table 3 illustrates the consequences of using a type A rather than type B national coefficient matrix. The most striking changes compared with Table 2 occur in Gyeongbuk: there is a big fall in the optimal δ from 0.6 to 0.35,

[6]We are grateful to Professors Zhao and Choi for letting us examine their data. This enabled us to verify that we were using the same sectoral classifications, national transactions matrix, employment data and LQs, yet we were still unable to replicate their findings.

TABLE 2 Reworking of Zhao and Choi's findings based on the same assumptions as Table 1

Formula	Region Daegu	Gyeongbuk
SLQ	42.70	66.97
CILQ	45.37	56.71
FLQ (δ = 0.3)	11.71	19.07
FLQ (δ = 0.35)	9.74	16.40
FLQ (δ = 0.4)	**9.20**	14.26
FLQ (δ = 0.45)	9.45	13.12
FLQ (δ = 0.5)	10.18	12.47
FLQ (δ = 0.55)	11.15	10.91
FLQ (δ = 0.6)	12.20	**10.49**
Optimal δ	0.4	0.6

Note: Optimal values are shown in bold type.

while the corresponding value of MAPE is cut from 10.5% to 6.5%. For Daegu, the optimal δ also falls, albeit less dramatically, from 0.4 to 0.35, while MAPE is lowered from 9.2% to 6.5%. It is remarkable how similar the results now are for the two regions. There is a further improvement in the performance of the SLQ and CILQ, although they are still far less accurate than the FLQ.

It is evident that Zhao and Choi (2015) have substantially overstated the required values of δ and understated the FLQ's accuracy. Also, even though the FLQ is still demonstrably more accurate than the SLQ and CILQ, the extent of this superiority is less marked than their results initially suggested.

4 | THE SECTOR-SPECIFIC APPROACH USING THE SFLQ

A key part of Zhao and Choi's study is a test of a new sector-specific FLQ formula, the SFLQ, devised by Kowalewski (2015). As explained earlier, this method involves using the regression model (10) to generate sector-specific values of δ for each region. Kowalewski's results for a German region are reproduced in Table 4, along with Zhao and Choi's Korean findings and our own estimates. For consistency, we computed the SLQ_j using sectoral employment data.

TABLE 3 Variant of Table 2 based on a type B rather than type A national coefficient matrix

Formula	Region Daegu	Gyeongbuk
SLQ	27.11	30.37
CILQ	27.11	26.39
FLQ (δ = 0.3)	6.82	6.91
FLQ (δ = 0.35)	**6.46**	**6.45**
FLQ (δ = 0.4)	7.07	6.62
FLQ (δ = 0.45)	8.16	7.21
FLQ (δ = 0.5)	9.40	8.22
FLQ (δ = 0.55)	10.44	9.79
FLQ (δ = 0.6)	11.41	11.79
Optimal δ	0.35	0.35

Note: Optimal values are shown in bold type.

Looking first at Kowalewski's results, it is striking how one of the regressors, CL_j, is highly statistically significant, whereas the remaining three have low t statistics. The positive estimated coefficient of CL_j is consistent with Kowalewski's argument that "the more an industry is concentrated in space, the higher the regional propensity to import goods or services of this industry" (Kowalewski, 2015, p. 248). Such industries would require a higher value of δ to adjust for this higher propensity. As expected, SLQ_j has a negative estimated coefficient. Kowalewski's rationale here is that "regional specialization would lead to an increase in intra-regional trade and a decrease in imports", so that "one would expect a higher SLQ_j to be accompanied by a lower value of δ_j, which would additionally (to the FLQ formula) dampen regional imports" (Kowalewski, 2015, p. 248). However, the t statistic for SLQ_j is very low, which suggests that this variable may not be relevant. Likewise, the results for both IM_j and VA_j cast doubt on their relevance.

Zhao and Choi's results are puzzling. Kowalewski's method requires a separate regression for each region since the values of SLQ_j would vary across regions. However, the authors report results for only one regression and offer no explanation as to how it was estimated or to which region it relates. Moreover, the estimated coefficient of CL_j is implausibly large and is markedly out of line with both Kowalewski's estimate and our own figures for Daegu and Gyeongbuk. The credibility of Zhao and Choi's results is also undermined by the fact that they were derived from a type A national coefficient matrix.

Turning now to our own regressions, the results for Daegu look sensible on the whole. The R^2 is only a little below that reported by Kowalewski. Moreover, CL_j is statistically significant at the 1% level and its estimated coefficient has the anticipated sign. Although SLQ_j and VA_j are still not significant at conventional levels, their t ratios are much better than in Kowalewski's regression. IM_j has a negligible t ratio in both regressions.

Our regression for Gyeongbuk leaves much to be desired in terms of both goodness of fit and the outcomes for CL_j and SLQ_j. However, a redeeming feature is the highly statistically significant result for VA_j. Kowalewski does not offer a rationale for including this variable but one might argue that a higher share of value added in total national output would mean a lower share of intermediate inputs and hence lower imports. If this effect were transmitted to regions, it is possible that a lower δ_j would be needed, i.e. $\beta_4 < 0$ in Equation 10.

Table 5 displays estimates of δ_j derived from our regressions, along with the 'optimal' values that would minimize MAPE for the type I output multipliers. To compute the optimal δ_j, we performed the calculations on a sectoral basis, using steps of 0.025 for δ, and then applied linear interpolation.

To evaluate our estimates, we correlated $\widehat{\delta}_j$ with δ_j. The simple correlation coefficient, r, was 0.739 (p = 0.000) for Daegu and 0.640 (p = 0.000) for Gyeongbuk. The fact that both correlations are highly statistically significant lends support to Kowalewski's approach, although there is clearly still much scope for enhanced accuracy. The difference in the size of r reflects the fact that Table 4 shows a higher R^2 for Daegu than for Gyeongbuk.

TABLE 4 Regression results based on Kowalewski's model (10)

			New results	
	Kowalewski	Zhao and Choi	Daegu	Gyeongbuk
Intercept	−0.009 (−0.08)	0.616 (17.5)	0.365 (2.74)	0.880 (6.12)
CL_j	1.266 (4.49)	10.635 (5.53)	0.541 (3.02)	−0.326 (−1.35)
SLQ_j	−0.025 (−0.38)	−0.214 (−5.45)	−0.086 (−1.66)	−0.018 (−0.41)
IM_j	−0.230 (−0.64)	3.352 (1.51)	−0.044 (−0.25)	−0.197 (−1.13)
VA_j	0.124 (1.12)	−0.247 (−0.51)	−0.253 (−1.68)	−0.830 (−3.82)
R^2	0.67	0.511	0.631	0.410
n	21		26	27

Note: t statistics are in brackets. Sector 7 was omitted from the Daegu regression.

Source: Kowalewski (2015, table 8); Zhao and Choi (2015, table 2).

TABLE 5 New results using Kowalewski's sector-specific approach

Sector	Description	Daegu		Gyeongbuk	
		δ_j	$\widehat{\delta}_j$	δ_j	$\widehat{\delta}_j$
1	Agriculture, forestry and fishing	0.588	0.447	0.157	0.206
2	Mining and quarrying	0.516	0.484	0.098	0.202
3	Food, beverages and tobacco products	0.329	0.351	0.288	0.511
4	Textiles and apparel	0.353	0.209	0.297	0.498
5	Wood and paper products	0.231	0.381	0.386	0.485
6	Printing and reproduction of recorded media	0.297	0.301	0.348	0.436
7	Petroleum and coal products	0.000	0.475	0.369	0.314
8	Chemicals, drugs and medicines	0.430	0.384	0.454	0.529
9	Non-metallic mineral products	0.379	0.424	0.623	0.433
10	Basic metal products	0.404	0.440	0.611	0.482
11	Fabricated metal products except machinery and furniture	0.252	0.282	0.674	0.493
12	General machinery and equipment	0.294	0.364	0.577	0.511
13	Electronic and electrical equipment	0.358	0.442	0.660	0.439
14	Precision instruments	0.297	0.296	0.578	0.512
15	Transportation equipment	0.359	0.419	0.518	0.535
16	Furniture and other manufactured products	0.545	0.332	0.243	0.528
17	Electricity, gas, steam and water supply	0.317	0.259	0.297	0.357
18	Construction	0.297	0.218	0.607	0.449
19	Wholesale and retail trade	0.091	0.156	0.411	0.331
20	Accommodation and food services	0.221	0.196	0.564	0.498
21	Transportation	0.249	0.203	0.353	0.412
22	Communications and broadcasting	0.184	0.220	0.325	0.407
23	Finance and insurance	0.049	0.180	0.035	0.294
24	Real estate and business services	0.275	0.237	0.488	0.222
25	Public administration and defence	0.100	0.166	0.202	0.222
26	Education, health and social work	0.098	0.120	0.399	0.263
27	Other services	0.160	0.164	0.401	0.428
Mean		0.284	0.284	0.407	0.407

Notes: δ_j is the value that minimizes MAPE for the sectoral multipliers, whereas $\widehat{\delta}_j$ is from the new results in Table 4. Sector 28 had to be omitted owing to missing data.

Source: Authors' own calculations.

The relative performance of the SFLQ in terms of MAPE is examined in Table 6. The table distinguishes between optimal values and regression-based estimates. Based on the optimal values, a residual error of about 2% would remain in each region. However, analysts using non-survey methods would not know the optimal values, so the results illustrate the best outcomes that could be attained with the SFLQ in a perfect world. More realistically, Table 6 records a MAPE of 4.7% in Daegu and 5.2% in Gyeongbuk. With δ = 0.35, the potential gains from using the SFLQ rather than the FLQ would be 1.8 percentage points in Daegu and 1.25 in Gyeongbuk.

In discussing their findings, Zhao and Choi (2015, p. 913) comment that it is "undeniable that SFLQ presents an extraordinary ability to minimize errors produced by regionalization." However, this statement is based on a comparison with results derived using optimal values. We would argue that the only relevant comparison is with regression-based estimates, which would be the only information potentially available to an analyst using non-survey

TABLE 6 Estimating output multipliers for two South Korean regions in 2005 via different methods (evaluation using MAPE)

Method	Region Daegu	Gyeongbuk
SLQ, Table 3	27.11	30.37
CILQ, Table 3	27.11	26.39
FLQ (δ = 0.35), Table 3	6.46	6.45
SFLQ (optimal δ_j), Table 5	1.85	2.04
SFLQ (estimated δ_j), Table 5	4.66	5.20
SFLQ (estimated δ_j), Equation 15	8.00	5.37
SFLQ (optimal δ_j), Zhao and Choi	2.885	2.121
SFLQ (estimated δ_j), Zhao and Choi	19.536	15.719

Source: Authors' own calculations; Zhao and Choi (2015, tables 4 and 5).

data. Clearly, with a MAPE of 19.5% for Daegu and 15.7% for Gyeongbuk, Zhao and Choi's results would not be helpful in that respect.

The results so far indicate that the SFLQ approach could yield a useful, albeit modest, enhancement of accuracy relative to the FLQ if used in conjunction with a well-specified regression model. Zhao and Choi (2015, p. 915) suggest that possible ways of refining these regressions could include: (i) introducing new explanatory variables; and (ii) using non-linear formulations. Unfortunately, it is hard to think of new variables for which data would be readily available. As regards refinement (ii), we considered the following alternative non-linear models:

$$\ln \delta_j = a + b_1 CL_j + b_2 SLQ_j + b_3 IM_j + b_4 VA_j + e_j \tag{13}$$

$$\ln \delta_j = c + d_1 \ln CL_j + d_2 \ln SLQ_j + d_3 \ln IM_j + d_4 \ln VA_j + f_j. \tag{14}$$

Table 7 reports a mixed outcome: the linear model (10) is best for Daegu, whereas the double-log model (14) is best for Gyeongbuk. However, the differences in performance of the three models are not substantial.

Nevertheless, there is a fundamental problem inherent in using the SFLQ: as noted earlier, analysts employing non-survey methods would not know the optimal values, so would be unable to fit a region-specific regression like those shown in Table 4. Furthermore, when we fitted Kowalewski's regression model to data for the other South Korean regions, we found that the results were unstable in terms of goodness of fit, the values of regression coefficients, and which variables were statistically significant. This instability suggests that it would be inadvisable to attempt to transfer results from one region to another.

It is evident that the need to use some region-specific data is an obstacle to the application of Kowalewski's approach. For this reason, we modified her regression model (10) by imposing the restriction β_2 = 0 and re-expressing

TABLE 7 Estimating output multipliers for two South Korean regions in 2005 using alternative forms of Kowalewski's regression model (evaluation using MAPE)

Method	Region Daegu	Gyeongbuk
Linear model (10), Table 6	4.66	5.20
Semi-log model (13)	4.89	4.99
Double-log model (14)	4.72	4.52

Source: Authors' own calculations (n = 27).

the dependent variable as the mean value of δ_j across all regions. SLQ_j was excluded on the basis that it is a region-specific variable.

Fitting the revised model to data for 27 sectors and 16 regions gave the following result:

$$\delta_j = 0.669 + 0.269\, CL_j - 0.403\, IM_j - 0.628\, VA_j + e_j, \tag{15}$$

where e_j is a residual. IM_j is highly statistically significant (t = −3.54; p = 0.002) and so too is VA_j (t = −4.57; p = 0.000), whereas CL_j is only marginally significant (t = 1.77; p = 0.090). CL_j has a positive coefficient, as anticipated, yet its modest t ratio is rather surprising. Since the role of this variable is to capture any regional imbalances in employment in sector j, we expected it to be more significant. The R^2 = 0.589 reflects both the omission of relevant explanatory variables and random variation in the values of δ_j.

We now need to assess the performance of Equation 15. Table 6 shows an evaluation in terms of MAPE. The results for Daegu are not encouraging: MAPE is 6.5% for the FLQ (with δ = 0.35), yet 8.0% for the SFLQ. By contrast, for Gyeongbuk, MAPE is 6.5% for the FLQ but 5.4% for the SFLQ.

However, when assessing the relative accuracy of the SFLQ and FLQ, we should also consider the number of parameters, k, to be estimated in each case. For the SFLQ, 27 sector-specific values of δ are required, so k = 27. By contrast, k = 1 for the FLQ. This aspect can be incorporated into the analysis via criteria such as the Bayesian information criterion (BIC) or Akaike's information criterion (AIC), whereby the number of parameters is penalized to avoid the ‘overfitting’ of models (Burnham & Anderson, 2004).

The BIC is defined here as:

$$BIC = n \times \ln\left(\widehat{\sigma}^2\right) + k \times \ln(n), \tag{16}$$

where n is the number of observations, k is the number of parameters and $\widehat{\sigma}^2$ is the variance of the estimated sectoral multipliers, namely $\widehat{\sigma}^2 = (1/n)\, \Sigma_j \left(\widehat{m}_j - m_j\right)^2$. AIC and BIC differ in one key respect: for $n > 2$, AIC imposes a smaller penalty for extra parameters. It is defined here as:

$$AIC = n \times \ln\left(\widehat{\sigma}^2\right) + k \times 2. \tag{17}$$

As k rises, with given n, BIC and AIC increasingly diverge, as BIC imposes a rising penalty for extra parameters. In this instance, given $\widehat{\sigma}^2 < 1$, the optimal value typically will be negative, so we will be looking for the most negative AIC or BIC. Using BIC or AIC rather than MAPE or $\widehat{\sigma}^2$ to compare regionalization methods will generally indicate one involving fewer parameters.

Table 8 reveals that, once we consider the number of parameters, and focus on the regression-based results, the FLQ convincingly outperforms the SFLQ. This outcome suggests that the enhanced precision gained by capturing the intersectoral dispersion in the values of δ is outweighed by the statistical uncertainty entailed by having to estimate 27 parameters rather than only one. As expected, BIC yields more pronounced differences in performance than does AIC.

An interesting question now arises: would it be possible to refine the regression model to the extent that the SFLQ gave more accurate estimates than the FLQ? For the BIC results in Table 8, the answer is definitely no. Even with R^2 = 1, the best attainable result for Daegu would be BIC = −89.550, which is clearly inferior to the −119.024 for the FLQ with δ = 0.35. The same outcome would occur in Gyeongbuk. In terms of AIC, we can see that the SFLQ with an ideal regression would outperform the FLQ in Daegu, albeit not very convincingly, but slightly underperform in Gyeongbuk. However, building such a regression is obviously unrealistic. In the light of these results, therefore, we would not recommend using the SFLQ.

TABLE 8 Estimating output multipliers for two South Korean regions in 2005 via different methods (evaluation using BIC and AIC)

		Region			
		Daegu		Gyeongbuk	
Method	*k*	BIC	AIC	BIC	AIC
SLQ, Table 3	0	−59.869	−59.869	−77.033	−77.033
CILQ, Table 3	0	−65.661	−65.661	−64.521	−64.521
FLQ (δ = 0.35), Table 3	1	**−119.024**	−120.356	**−125.614**	**−126.946**
SFLQ (optimal δ_j), Table 5	27	−89.550	**−124.537**	−90.126	−125.114
SFLQ (estimated δ_j), Table 5	27	−48.474	−83.461	−45.347	−80.335
SFLQ (estimated δ_j), Equation 15	27	−27.043	−62.031	−42.144	−77.132

Note: Optimal values are shown in bold type.

Source: Authors' own calculations (n = 27 for the SFLQ; 28 otherwise).

5 | EXTENSION TO ALL REGIONS

5.1 | Results for 16 regions

In this section, we expand our analysis to encompass all 16 South Korean regions, which should help to identify results that are more generally valid, particularly in terms of finding appropriate values for δ. Before considering our findings, it may be helpful to examine the key regional characteristics presented in Table 9.

Table 9 examines two alternative ways of measuring regional size. Although one can see at a glance that the output and employment shares are not perfectly matched, there is agreement that Gyeonggi-do and Seoul are the two biggest regions and that Jeju-do is the smallest. Even so, the strong correlation (r = 0.921) between the output and employment shares may mask much variability in productivity at the sectoral level. Consequently, we opted to use the regional share of gross output, S_o, as our preferred measure of regional size.

Correlation analysis offers a convenient way of exploring the relationship between S_o and the other variables in Table 9. As anticipated by the FLQ approach, there is a positive association between S_o and the intraregional share of inputs (r = 0.557; p = 0.025) and a negative one between S_o and the share of inputs from other regions (r = −0.508; p = 0.045).

Nevertheless, what is most striking about the data in Table 9 is the marked interregional variation in the share of foreign inputs in gross output, S_f, which poses some challenges for the FLQ approach. Ulsan stands out as having an especially high share of inputs from abroad. It is interesting that S_f is strongly negatively correlated (r = −0.932; p = 0.000) with the share of value added, S_v, yet it is not significantly correlated (at the 5% level) with any other variable. S_v, in turn, is not significantly correlated with any other variable.

Herfindahl's index, $H_r = \Sigma_i \left(Q_i^r / \Sigma_i Q_i^r\right)^2$, where Q_i^r is the output of sector i in region r, measures the extent to which each region's output is concentrated in one or more sectors. Ulsan again stands out as having an unusually high value for H_r. However, apart from Seoul, Gyeongbuk and Jeollanam-do, the values of H_r are fairly close to the mean. It is worth noting that H_r is significantly correlated with both the share of inputs from abroad (r = 0.638; p = 0.008) and the share from other regions (r = −0.567; p = 0.022).

The minimum MAPE in each region is identified in bold in Table 10, along with the corresponding optimal δ.[7] It should be noted that these calculations do not take into account possible intersectoral variation in the values of δ

[7]The results for Daegu and Gyeongbuk in Tables 3 and 10 differ because we used sectoral output data for Table 10 but employment data for Table 3. We also used our own calculations of benchmark multipliers for Table 10 but the Bank of Korea's figures for Table 3.

TABLE 9 Characteristics of South Korean regions in 2005

	Region	Output (%)	Employment (%)	Share of inputs from within region	Share of inputs from other regions	Share of inputs from abroad	Share of value added in output	Herfindahl's index (H_r)
1	Gyeonggi-do	20.1	20.2	0.226	0.245	0.120	0.410	0.070
2	Seoul	18.2	25.4	0.237	0.173	0.060	0.529	0.112
3	Gyeongbuk	8.4	5.4	0.247	0.254	0.163	0.336	0.125
4	Gyeongsangnam-do	7.3	6.7	0.223	0.284	0.125	0.369	0.065
5	Ulsan	7.1	2.5	0.202	0.240	0.283	0.275	0.178
6	Jeollanam-do	6.5	3.3	0.288	0.163	0.219	0.331	0.123
7	Chungcheongnam-do	6.3	3.9	0.201	0.274	0.177	0.348	0.070
8	Incheon	5.5	4.8	0.175	0.288	0.171	0.366	0.058
9	Busan	5.1	7.4	0.200	0.266	0.077	0.457	0.060
10	Chungcheongsbuk-do	2.9	3.0	0.181	0.307	0.104	0.408	0.068
11	Daegu	2.9	4.7	0.189	0.279	0.061	0.472	0.061
12	Jeollabuk-do	2.7	3.2	0.192	0.304	0.074	0.430	0.067
13	Gangwon-do	2.2	2.9	0.198	0.230	0.044	0.528	0.077
14	Gwangju	2.2	2.8	0.165	0.307	0.099	0.430	0.077
15	Daejeon	1.9	2.7	0.133	0.281	0.065	0.520	0.077
16	Jeju-do	0.7	1.1	0.172	0.253	0.039	0.536	0.085
Mean		6.25	6.25	0.202	0.259	0.118	0.422	0.086
V		0.89	1.08	0.18	0.16	0.58	0.20	0.38

Note: Shares are expressed as a proportion of gross output. *V* is the coefficient of variation.

Source: Authors' own calculations for H_r and the shares of gross output.

TABLE 10 Estimating output multipliers for South Korean regions in 2005 using the FLQ with different values of δ (MAPE based on 28 sectors)

		Value of δ						
	Region	**0.2**	**0.25**	**0.3**	**0.35**	**0.4**	**0.45**	**0.5**
1	Gyeonggi-do	14.03	11.47	9.19	7.07	5.65	4.74	**4.21***
2	Seoul	6.91	6.66	6.57	**6.54**	6.60	6.70	6.84
3	Gyeongbuk	10.23	8.30	6.73	5.99	**5.76**	6.06	6.48
4	Gyeongsangnam-do	9.32	7.25	6.17	5.46	**5.41**	6.03	7.15
5	Ulsan	15.09	13.54	12.11	10.77	9.58	8.67	**8.30***
6	Jeollanam-do	13.54	12.58	12.04	11.71	11.56	**11.54**	11.56
7	Chungcheongnam-do	15.94	13.28	10.55	8.41	7.09	**6.65**	6.66
8	Incheon	16.54	12.93	9.50	7.34	5.95	**5.40**	5.71
9	Busan	8.89	6.83	6.21	**6.05**	6.82	7.98	9.18
10	Chungcheongsbuk-do	9.72	8.51	7.72	**7.59**	7.80	8.65	9.97
11	Daegu	8.03	6.59	**6.14**	6.65	7.79	9.03	10.10
12	Jeollabuk-do	11.82	10.38	9.59	9.18	**9.15**	9.33	9.90
13	Gangwon-do	**8.94**	9.17	9.74	10.50	11.26	12.08	12.74
14	Gwangju	10.36	8.17	7.06	**6.74**	6.98	7.73	8.44
15	Daejeon	12.92	11.02	9.78	9.00	8.34	7.82	**7.57**
16	Jeju-do	**10.28**	10.69	11.17	11.64	11.99	12.41	12.73
Mean		11.41	9.84	8.77	8.16	**7.98**	8.18	8.60

Note: *For these regions, the optimum occurs at δ > 0.5. Optimal values are shown in bold type.

Source: Authors' own calculations.

in each region. There is much interregional variation in these optimal values, yet it is also true that ten of them lie in the range 0.4 ± 0.05, where MAPE is about 8%. Gangwon-do and Jeju-do are atypical in requiring δ = 0.2, whereas three regions need at least δ = 0.5.[8] Looking at the overall pattern of results, there does seem to be some tendency for the optimal δ to rise with regional size.

5.2 | Sensitivity analysis using different criteria

The simulations thus far have been evaluated primarily in terms of MAPE, thereby facilitating comparisons with the work of Zhao and Choi (2015). Although MAPE has some desirable properties as a criterion, it does not capture all aspects relevant to the choice of method. It is desirable, therefore, to employ a range of criteria with different properties. In line with previous research (Flegg et al., 2016; Flegg & Tohmo, 2013a, 2016), the following additional statistics will be employed to evaluate the estimated multipliers:

$$\text{MPE} = (100/28)\sum_j \left(\widehat{m}_j - m_j\right)/m_j, \tag{18}$$

$$\text{WMPE} = 100\sum_j w_j \left(\widehat{m}_j - m_j\right)/m_j, \tag{19}$$

$$\text{S} = \left\{\text{sd}\left(\widehat{m}_j\right) - \text{sd}\left(m_j\right)\right\}^2, \tag{20}$$

$$U = 100\sqrt{\frac{\sum_j \left(\widehat{m}_j - m_j\right)^2}{\sum_j {m_j}^2}}. \tag{21}$$

[8]The optimal δ is approximately 0.534 for Gyeonggi-do, 0.542 for Ulsan and 0.497 for Daejeon.

TABLE 11 Estimating output multipliers for South Korean regions in 2005 via different methods and criteria (16 regions and 28 sectors)

Method	Criterion MAPE	MPE	WMPE	$S \times 10^3$	*U*
SLQ	22.224	21.210	24.374	20.078	26.529
CILQ	23.541	22.386	19.136	14.837	26.706
FLQ (δ = 0.2)	11.411	8.767	5.780	2.316	13.911
FLQ (δ = 0.25)	9.836	5.998	3.007	1.298	12.114
FLQ (δ = 0.3)	8.768	3.463	**0.500**	0.701	10.903
FLQ (δ = 0.325)	8.424	2.297	−0.642	0.552	10.538
FLQ (δ = 0.35)	8.164	1.190	−1.710	0.461	10.322
FLQ (δ = 0.375)	8.022	**−0.143**	−2.699	**0.428**	**10.237**
FLQ (δ = 0.4)	**7.984**	−0.848	−3.615	0.435	10.256
FLQ (δ = 0.425)	8.038	−1.788	−4.471	0.483	10.370

Note: Optimal values are shown in bold type.

Source: Authors' own calculations based on the unweighted mean of results for 16 regions.

MPE is the mean percentage error. This statistic has been included since it offers a convenient way of measuring the amount of bias in a relative sense. It has also been used in many previous studies. WMAE is the weighted mean percentage error, which takes into account the relative importance of each sector. w_j is the proportion of total regional output produced in sector *j*. The role of the squared difference in standard deviations (S) is to assess how far each method is able to replicate the dispersion of the benchmark distribution of multipliers. Finally, *U* is Theil's well-known inequality index, which has the merit that it encompasses both bias and variance (Theil, Beerens, DeLeeuw, & Tilanus, 1966). A demerit of *U* is, however, that the use of squared differences has the effect of emphasizing any large positive or negative errors and thereby skewing the results.

Table 11 reveals a high degree of consistency in the results across different criteria. Regardless of which criterion is used, the SLQ and CILQ yield comparable outcomes and both perform very poorly indeed relative to the FLQ. MPE shows, for example, that the SLQ overstates the sectoral multipliers by 21.2% on average across the 16 regions, whereas the FLQ with δ = 0.375 exhibits negligible bias. Furthermore, δ = 0.375 gives MAPE = 8.0%, which is well below the outcomes for the SLQ and CILQ.

Since MPE, S and *U* all indicate $\delta \approx 0.375$, this suggests that there is no conflict between minimizing bias and variance in this data set. However, one should note that WMPE indicates an optimum of δ = 0.3, so $\delta < 0.375$ may be needed for the relatively larger sectors.

The discussion so far has been conducted solely in terms of multipliers, so it is worth considering briefly whether different findings would emerge from an analysis of input coefficients.[9] A selection of results is presented in Table 12.

Tables 11 and 12 reveal a very similar pattern in terms of the approximate optimal values of δ; this feature is especially noticeable for the WMPE and *U* criteria. Even so, for a given δ, the estimated coefficients are clearly much more prone to error than are the corresponding estimated multipliers. For instance, for δ = 0.375, MAPE is 8.0% for multipliers but 44.9% for coefficients. This well-known phenomenon arises because the elements in the difference matrix, $\mathbf{D} = \left[\hat{r}_{ij} - r_{ij}\right]$, are bound to exhibit far more dispersion than is true for the errors in the column sums of the Leontief inverse matrix, $\mathbf{d}' = \left[\hat{m}_j - m_j\right]$; much offsetting of errors occurs when computing multipliers (Flegg & Tohmo, 2013a). It is also worth noting that the results in Table 12 confirm the previous finding for multipliers that the FLQ's performance far surpasses that of the SLQ and CILQ.

[9]Typically, the ranking of methods is not materially affected by whether one examines multipliers or input coefficients. See, for example, Flegg and Tohmo (2016).

TABLE 12 Estimating input coefficients for South Korean regions in 2005 via different methods and criteria (16 regions and 28 sectors)

Method	Criterion				
	MAPE	MPE	WMPE	S × 10^3	*U*
SLQ	85.002	−78.509	87.945	3.538	82.462
CILQ	89.904	−91.600	70.797	3.102	89.117
FLQ (δ = 0.2)	59.903	−46.810	25.000	1.304	56.487
FLQ (δ = 0.25)	53.732	−36.111	13.942	0.405	51.583
FLQ (δ = 0.3)	49.057	−25.758	3.279	0.283	48.307
FLQ (δ = 0.325)	57.326	−20.774	**−1.121**	0.255	47.367
FLQ (δ = 0.35)	45.948	−15.904	−6.118	0.236	46.863
FLQ (δ = 0.375)	44.940	−11.170	−11.006	0.231	**46.750**
FLQ (δ = 0.4)	44.200	−6.527	−14.476	**0.229**	46.911
FLQ (δ = 0.425)	**41.821**	**2.418**	−18.570	0.238	50.496

Note: Optimal values are shown in bold type.

Source: Authors' own calculations based on the unweighted mean of results for 16 regions.

5.3 | Choosing values for δ

Although the results presented earlier offer some guidance regarding appropriate values of δ, it would be helpful if a suitable estimating equation could be developed. With this aim in mind, Flegg and Tohmo (2013a) fitted the following model to survey-based data for twenty Finnish regions in 1995:

$$\ln \delta = -1.8379 + 0.33195\ \ln R + 1.5834\ \ln P - 2.8812\ \ln I + e, \tag{22}$$

where *R* is regional size measured in terms of output and expressed as a percentage; *P* is the proportion of each region's gross output imported from other regions, averaged over all sectors and divided by the mean for all regions; *I* is each region's average use of intermediate inputs (including inputs from other regions), divided by the corresponding national average; *e* is a residual. Observations on ln δ were derived by finding the value of δ that minimized MPE for each Finnish region. R^2 = 0.915 and all three regressors were highly statistically significant. The model comfortably passed all χ^2 diagnostic tests.

Table 13 records the results of our re-estimation of Flegg and Tohmo's model using data for all 16 South Korean regions.[10] Observations on ln δ were derived by finding the value of δ that minimized MAPE for each region.[11] Regression (1) has the same specification as Equation 22 and the corresponding estimated elasticities have identical signs. However, in terms of the usual statistical criteria, this new model is less satisfactory than the Finnish one. We therefore attempted to refine it by adding a new regressor, ln *F*, where *F* is the average proportion of each region's gross output imported from abroad, divided by the mean for all regions. As illustrated in Table 9, the share of foreign imports in gross output varies greatly across regions, so this variable should be relevant.

It is evident that ln *F* adds greatly to the model's explanatory power and its estimated coefficient has the anticipated sign. However, the χ^2 statistic reveals that the residuals are not normally distributed. Daejeon was identified as the main source of this problem: its residual is more than two standard errors from zero. To address

[10]Zhao and Choi (2015, table 2) report the results of estimating, using South Korean data, what they refer to as 'Flegg's model'. However, this regression has an R^2 = 0.003 and regional size, *R*, is the sole explanatory variable. How this result was obtained is not explained. By contrast, when we regressed ln δ on ln *R* alone, R^2 = 0.394.

[11]To estimate a value yielding the minimum MAPE in each region, we varied δ in steps of 0.0001.

TABLE 13 Alternative regression models to estimate δ using data for 16 South Korean regions in 2005

	(1)	(2)	(3)	(4)
Intercept	−1.290 (−9.85)	−1.143 (−9.26)	−1.227 (−19.1)	−1.226 (−20.1)
ln R	0.261 (3.65)	0.112 (1.34)	0.169 (3.87)	0.168 (4.80)
ln P	0.462 (1.37)	0.361 (1.28)	0.325 (2.26)	0.325 (2.37)
ln I	−2.231 (−1.41)	1.097 (0.59)	−0.024 (−0.02)	-
ln F	-	0.351 (2.52)	0.316 (4.45)	0.317 (6.64)
B_{15}	-	-	0.577 (5.72)	0.577 (6.12)
R^2	0.555	0.718	0.934	0.934
AIC	−0.058	2.595	13.208	14.207
χ^2 (1) functional form	1.419	0.867	0.256	0.123
χ^2 (2) normality	4.013	19.257	0.002	0.002
χ^2 (1) heteroscedasticity	2.796	0.530	0.006	0.006

Notes: t statistics are in brackets. AIC is Akaike's information criterion. The critical values of χ^2 (1) and χ^2 (2) at the 5% level are 3.841 and 5.991, respectively.

Source: Authors' own calculations.

this problem, and to prevent this outlier from distorting the results, a binary variable, B_{15}, was added to the model.[12] Regression (3) records the outcome.

The χ^2 statistic now shows no discernible skewness and kurtosis in the residuals. The big rise in R^2 reflects the fact that B_{15} is highly statistically significant. There is also a marked rise in the t ratios for ln R, ln P and ln F. However, the results strongly suggest that ln I is redundant, so it has been omitted from regression (4). This regression now has the highest AIC, hence the best fit.[13] It also has the best t ratios and comfortably passes all χ^2 diagnostic tests. Although regression (4) differs in several respects from the Finnish Equation 22, these dissimilarities can largely be explained by the differences between Finland and South Korea in the amount of interregional variation in each variable.[14]

Before assessing how well regression (4) can estimate δ for individual regions, it is worth examining an alternative approach proposed by Bonfiglio (2009), who used simulated data from a Monte Carlo study to derive the following regression equation:

$$\widehat{\delta} = 0.994\,PROP - 2.819\,RSRP, \tag{23}$$

where *PROP* is the propensity to interregional trade (the proportion of a region's total intermediate inputs bought from other regions) and *RSRP* is the relative size of regional purchases (the ratio of total regional to total national intermediate inputs). The principal advantage of a Monte Carlo approach, according to Flegg et al. (2016, p. 33), lies in the generality of the findings, whereas "the results derived from a single region may reflect the peculiarities of that region and thus not be valid in general." However, with data for 16 regions, concerns about a lack of generality are less compelling here, although there remains the possibility that South Korea is a unique case.

[12]B_{15} = 1 for Daejeon and zero otherwise. As the second smallest region, Daejeon is atypical in the sense that it requires an unusually high value of $\delta \approx 0.5$. Without B_{15}, $\widehat{\delta} = 0.306$ for this region.

[13]AIC = ln L − (k + 1), where ln L is the maximized log-likelihood of the regression and k is the number of regressors. Compared with the more conventional $\overline{R}^2$, AIC takes more account of k.

[14]Although we tried to refine the regressions by adding ln H, where H is Herfindahl's index of concentration, ln H always had a negligible t ratio. The likely explanation is that H varies little across regions (see Table 9). Flegg and Tohmo (2013a, note 26) report a similar outcome for Finland.

TABLE 14 Alternative ways of estimating δ for 16 South Korean regions in 2005

	δ Minimum MAPE	$\hat{\delta}$ Table 13, regression (4)	$\hat{\delta}$ Bonfiglio's method
Gyeonggi-do	0.534	0.481	−0.156
Seoul	0.337	0.336	−0.147
Gyeongbuk	0.401	0.469	0.142
Gyeongsangnam-do	0.389	0.433	0.239
Ulsan	0.542	0.543	0.129
Jeollanam-do	0.441	0.434	0.059
Chungcheongnam-do	0.470	0.472	0.240
Incheon	0.438	0.463	0.297
Busan	0.344	0.339	0.344
Chungcheongsbuk-do	0.347	0.360	0.434
Daegu	0.297	0.289	0.444
Jeollabuk-do	0.370	0.316	0.454
Gangwon-do	0.212	0.234	0.423
Gwangju	0.340	0.336	0.474
Daejeon	0.497	0.497	0.528
Jeju-do	0.196	0.191	0.522
Mean	0.385	0.387	0.277
MAPE (multipliers)	7.226	7.334	

Source: Authors' own calculations.

The first column in Table 14 displays the optimal values of δ, those that minimize MAPE for the sectoral multipliers, while the second column records the predicted values from regression (4) in Table 13. There is a very close correspondence between the two sets of values, with $r = 0.957$ ($p = 0.000$). This outcome reflects the high R^2 of regression (4). By contrast, Bonfiglio's method gives very poor estimates of δ and there is a negative, rather than positive, correlation between $\hat{\delta}$ and δ, with $r = -0.485$ ($p = 0.057$).[15] Moreover, $\hat{\delta} < 0$ for the two largest regions, which contradicts the theoretical restriction $\delta \geq 0$. Flegg et al. (2016, p. 33) note that $\hat{\delta} < 0$ can occur where regions are relatively large or exhibit below-average propensities to import from other regions or have both characteristics. Given these problems, we would not recommend the use of Bonfiglio's method.[16]

Regarding Flegg and Tohmo's method, the way in which regression (4) in Table 13 is specified should make it easier for an analyst to estimate δ. The regression, with $B_{15} = 0$, is reproduced below:

$$\ln\delta = 1.2263 + 0.1680\ \ln R + 0.3254\ \ln P + 0.3170\ \ln F + e. \tag{24}$$

An analyst would need to make an informed assumption about how far a region's propensity to import from other regions diverged from the mean for all regions in a country, which should be easier than having to measure this propensity directly. Likewise, an allowance could be made for any assumed divergence between the regional and national shares of foreign inputs. It would also be easy to carry out a sensitivity analysis. However, in some cases, it might be more convenient to employ the following variant of Equation 24:

$$\ln\delta = -3.0665 + 0.1680\ \ln R + 0.3254\ \ln p + 0.3170\ \ln f + e, \tag{25}$$

[15]We used output shares (see Table 9) to proxy *RSRP*. For *PROP*, we used the ratio A/B, where A represents imports from other South Korean regions, and B = A + intraregional intermediate inputs + imports from abroad.

[16]For a more detailed evaluation of Bonfiglio's method, see Flegg et al. (2016, pp. 33–34).

where p is each region's propensity to import from other regions and f is each region's average use of foreign intermediate inputs, both measured as a proportion of gross output.

To evaluate regression (4) in terms of sectoral multipliers, again consider Table 14, where the estimated δ for each region was used to compute sectoral multipliers and hence MAPE. The results were then averaged over all regions to get MAPE ≈ 7.3%. By contrast, Table 11 reveals that using $\delta = 0.375$ for all regions would give MAPE ≈ 8.0%, which represents a potential gain of about 0.7 percentage points, on average, from using the region-specific estimates.

6 | CONCLUSION

This paper has employed survey-based data for 16 South Korean regions to refine the application of the FLQ formula for estimating regional input coefficients. The focus was on the choice of values for the key unknown parameter δ in this formula.

Several important findings emerged from our statistical analysis. For instance, on average across the 16 regions, the FLQ with $\delta = 0.375$ gave a mean absolute percentage error (MAPE) of 8.0% for the type I sectoral output multipliers, compared with 23.5% for the CILQ and 22.2% for the SLQ. The corresponding mean percentage error was −0.1% for the FLQ, yet 22.4% for the CILQ and 21.2% for the SLQ. Although it is unsurprising that the CILQ and SLQ should yield overstated multipliers, the size of this bias is striking. The credibility of these findings is bolstered by the fact that they were confirmed by Theil's inequality index, which takes both bias and dispersion into account.

So as to enhance the FLQ's accuracy, we employed the South Korean dataset to develop a regression model that could potentially be used by analysts to refine their choice of a value for δ. We included regressors to capture regional size and the propensities to import from other regions and from abroad. We found that interregional variation in the propensity to import from abroad played a key role in determining the value of δ. The model satisfied a range of statistical criteria and gave relatively accurate estimates of δ. On average, its use to derive region-specific estimates of δ lowered MAPE by some 0.7 percentage points, when compared with the use of a single δ across all regions.

We also considered in detail the proposed sector-specific approach of Kowalewski (2015), which aims to enhance the accuracy of the FLQ by permitting δ to vary across sectors. Her SFLQ approach employs a regression model to estimate a δ for each sector j in a region. We first fitted this model to data for two South Korean regions, using as regressors a region-specific variable, SLQ_j, and three other variables based on national data. The model worked fairly well in one region but less so in the other. We then excluded SLQ_j and reran the regression using data for all 16 regions simultaneously. The aim here was to produce a more useful general model based on readily available national data.

The general model produced mixed results: for example, relative to the FLQ with $\delta = 0.35$, MAPE was cut by 1.1 percentage points in one region but raised by 1.5 percentage points in the other. As the accuracy of the SFLQ depends crucially on the regression model used to estimate the δ_j, more research is clearly needed to improve its specification.

However, a more fundamental concern was raised regarding the SFLQ approach: whereas the FLQ requires the estimation (or assumption) of a single value of δ, the SFLQ calls for the estimation of a δ for every sector. This requirement introduces a new element of statistical uncertainty. Using the AIC and BIC criteria, we found that the extra accuracy gained by permitting δ to vary across sectors was outweighed by the need to estimate numerous extra parameters. Consequently, we would question the use of the SFLQ in a practical context.

It seems fair to conclude that the findings in this paper offer support for the FLQ's use as a regionalization technique. Moreover, interesting recent work by Hermannsson (2016) and Jahn (2017) has extended its use from an analysis of single regions to a multi-regional context. Nonetheless, as with all such pure non-survey methods, the FLQ can only be relied upon to give a satisfactory initial set of regional input coefficients. Analysts should always seek to refine these estimates via informed judgement, using any available superior data, carrying out surveys of key sectors and so on. Indeed, we would argue that the FLQ is very well suited to building the non-survey foundations of a hybrid model (Lahr, 1993).

It is worth noting, finally, that the analysis in this paper could be built upon in several ways. For instance, it would be interesting to employ the South Korean dataset in testing the multi-regional methodological framework developed by Jahn (2017). In addition, some useful insights might be gained by examining the impact on type II multipliers of cross-regional wage and consumption flows, as is done by Hermannsson (2016) in terms of Scottish data.

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Resumen. Este documento utiliza datos basados en encuestas de 16 regiones de Corea del Sur para refinar la aplicación del cociente de localización de Flegg (FLQ, por sus siglas en inglés) y su variante, el FLQ específico para un sector (SFLQ, por sus siglas en inglés). Estas regiones varían notablemente en términos de tamaño. Se presta especial atención al problema de elegir valores apropiados para el parámetro desconocido δ en estas fórmulas. Se evalúan y prueban enfoques alternativos a este problema. Este artículo se suma a investigaciones anteriores con el objetivo común de encontrar una forma eficaz en función del costo de adaptar los coeficientes nacionales, a fin de producir un conjunto inicial satisfactorio de coeficientes regionales de insumos para las regiones en las que no se dispone de datos basados en encuestas.

抄録: 本稿では、韓国の16の地域の調査に基づくデータを使用して、Fleggの立地係数法(Flegg's location quotient: FLQ)とその変形である、セクター特異的なFLQ (sector - specific FLQ:SFLQ)の応用を改良する。これらの地域は互いに規模に大きな差がある。これらの式の不明なパラメータ ▯ に適切な値を選択する上での問題に特に注意する。この問題への他のアプローチを評価してテストする。本研究は、調査に基づくデータのない地域でも申し分のない地域の入力係数を求めることができるよう、全国的な係数を調整する費用効果の良い方法を探索した先行研究の結果を更新する。