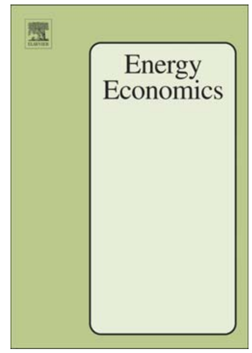

Multilevel index decomposition analysis: Approaches and application

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Multilevel index decomposition analysis: Approaches and application

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Abstract

With the growing interest in using the technique of index decomposition analysis (IDA) in energy and energy-related emission studies, such as to analyze the impacts of activity structure change or to track economy-wide energy efficiency trends, the conventional single-level IDA may not be able to meet certain needs in policy analysis. In this paper, some limitations of single-level IDA studies which can be addressed through applying multilevel decomposition analysis are discussed. We then introduce and compare two multilevel decomposition procedures, which are referred to as the multilevel-parallel (M-P) model and the multilevel-hierarchical (M-H) model. The former uses a similar decomposition procedure as in the single-level IDA, while the latter uses a stepwise decomposition procedure. Since the stepwise decomposition procedure is new in the IDA literature, the applicability of the popular IDA methods in the M-H model is discussed and cases where modifications are needed are explained. Numerical examples and application studies using the energy consumption data of the US and China are presented.

JEL: C43, Q43

Keywords: Index decomposition analysis; Multilevel decomposition analysis; Multi-hierarchical model; Energy intensity; Structure change.

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1. Introduction

Index decomposition analysis (IDA) has been widely used to study the driving forces behind aggregate energy consumption changes, sectoral and economy-wide energy efficiency trends, and differences between countries in energy consumption or carbon emissions. See, for example, Ang and Zhang (2000), EERE (2003), Bataille et al. (2007), IEA (2007), OEE (2009), and Ang et al., (2010). In economy-wide studies, total energy consumption is often given as a sum of consumption in various energy consuming sectors. Each sector in turns comprises subsectors and so on. This leads to a well-defined hierarchy of energy consumption data, where IDA studies can be conducted at different levels of sector disaggregation. Generally, changes in the aggregate energy consumption at a specific level are often decomposed to give the contributions of factors linked to overall activity change, activity structure shifts, and energy efficiency improvement. The choice of level may vary from one study to another due to differences in study scope and objective, or in data availability and quality.[1]

We refer to the IDA studies conducted at a specific level as those using a single-level decomposition model. Such studies, comprising the majority of IDA studies in the literature, give decomposition results meaningful for the chosen level. Take, for example, an energy consumption data hierarchy with two levels of sector disaggregation as shown in Fig. 1. Assume that the energy efficiency change at level 0 is the indicator of interest and is to be estimated using IDA. It can be obtained using either the data at level 1 or level 2. In each case, a single-level decomposition model will be used. Generally the results obtained at the two levels are different and the linkages between them are not formally established.

[Figure 1 here]

It is pointed out in the IDA literature that the energy intensity effect estimated at a finer level gives a better proxy for energy efficiency change. However, when the structure effect is studied using a single-level decomposition model, a finer level may lead to a higher degree of cancellation among sub-category effects (Ang, 1993). As a result, some compromise is needed in determining the “right” level to give representative

[1] Unless otherwise specified, the term “level” in the rest of the paper refers to level of disaggregation in a data hierarchy.

estimates of the structure and energy intensity effects in a single-level study. This makes the single-level analysis decomposition results somewhat specific.

Due to the above limitations, some IDA studies have reported the results obtained at several different levels of a data hierarchy. See, for example, Jenne and Cattell (1983), Boyd et al. (1987), Ang and Skea (1994), Sinton et al. (1994), and González et al. (2003). Since decomposition analyses in these studies were derived independently using single-level IDA models applied at different levels, the issues of consistency in result aggregation and interpretation arise.[2] To overcome these limitations, multilevel index decomposition analysis has been proposed. Some early studies include Li et al. (1990), Gardner (1993), Huang (1993), and Alam (2002). These studies all dealt with industrial energy use where industry subsectors are classified into the energy-intensive group and the non-energy-intensive group. Decomposition analysis was conducted based on a two-level energy consumption hierarchy to measure the contribution of activity shifts between the two industry groups, as well as among subsectors in each of these two groups.

Further improvements have been made in more recent multilevel studies. Ma and Stern (2008) study energy efficiency change in China using a three-level energy data hierarchy. It is shown that structure changes at more aggregate levels have increased China's industrial energy consumption, while structure changes at the finer level have contributed to a decrease. In Petrick (2013), changes in CO_2 emissions in Germany's industry are studied at the industry subsector level and plant level. The results show that both structure change at the subsector level and that at the plant level have contributed to reduce the CO_2 emissions. Multilevel index decomposition models have also been adopted in some national energy efficiency accounting systems, such as those developed by Canada (Bataille and Nyboer, 2005) and the United States (EERE, 2003).

These multilevel IDA studies reported in the literature are generally empirical studies. An analytical study that looks into the conceptual and methodological aspects is lacking. For instance, why shall we develop multilevel IDA models? What is the practical significance of applying multilevel IDA? In terms of IDA decomposition identity and procedure, what is the difference between multilevel IDA and single-level IDA? What are the methodological issues that are unique to multilevel studies? In this paper, we attempt to fill some of these research gaps.

[2] That is, whether the results obtained at a finer level can be consistently aggregated to give those obtained at a more aggregate level, and how differences between the results at different levels are to be interpreted.

In the rest of the paper, we start with a discussion on the limitations of single-level IDA in Section 2. Two different multilevel IDA models are thereafter introduced in Section 3 and 4. Section 5 presents two simple examples which reveal the main features of multilevel analysis. Section 6 discusses the applicability and some relevant methodological issues of popular IDA methods in the multilevel IDA context. Section 7 presents two case studies regarding the application of multilevel IDA. Section 8 concludes.

2. Single-level decomposition analysis

Refer to the energy consumption data hierarchy in Fig. 1. Let E be the energy consumption. The energy consumption at level 0, E^{L0}, may be written in terms of the variables defined at level 1 and level 2 respectively as follows:

$$E^{L0} = \sum_i E_i^{L1} = \sum_i A^{L0} \frac{A_i^{L1}}{A^{L0}} \frac{E_i^{L1}}{A_i^{L1}} = \sum_i A^{L0} S_i^{0,1} I_i^{L1} \quad (1)$$

$$E^{L0} = \sum_j E_j^{L2} = \sum_j A^{L0} \frac{A_j^{L2}}{A^{L0}} \frac{E_j^{L2}}{A_j^{L2}} = \sum_j A^{L0} S_j^{0,2} I_j^{L2} \quad (2)$$

where A denotes activity, S denotes activity structure, and I denotes energy intensity. The superscript indicates the level of disaggregation, and the subscripts i and j indicate the sub-categories at level 1 and level 2, respectively. In a multiplicative decomposition scheme, a change in the total energy consumption from time 0 to T, i.e. $D_{tot}^{L0} = E_T^{L0} / E_0^{L0}$, can be estimated at level 1 and level 2 as:

$$D_{tot}^{L0} = D_{act}^{L0} \cdot D_{str}^{0,1} \cdot D_{int}^{L1} \quad (3)$$

$$D_{tot}^{L0} = D_{act}^{L0} \cdot D_{str}^{0,2} \cdot D_{int}^{L2} \quad (4)$$

From both equations, the total energy consumption change at level 0 is decomposed into the contribution of the overall activity effect at level 0 (D_{act}^{L0}), and the structure effect ($D_{str}^{0,1}, D_{str}^{0,2}$) and energy intensity effect ($D_{int}^{L1}, D_{int}^{L2}$) at the respective disaggregate levels.[3]

According to the practices in the literature, the results for the structure effect and energy intensity effect estimated at level 1 and level 2 are usually not the same. Since

[3] For the sake of conciseness, we only provide the multiplicative decomposition formulae. Similar analysis can be conducted for an additive decomposition scheme.

energy intensities given at a more disaggregate level is a better proxy of energy efficiency, the energy intensity effect computed at level 2 is generally preferred if tracking energy efficiency trends is the objective. However, the structure effect computed at a finer level may not be necessarily better. This is due to the fact that the significance of a structure effect is closely linked to the level selected. For example, in an economy-wide study, activity structure change among main economic sectors will likely be used to capture possible transformation of an economy, while activity structure change among end-uses might be too detailed to provide information that is useful in this case. Furthermore, a very fine level may cause substantial cancellation of the impacts of structure shifts. As a result, the results obtained can be ambiguous unless further analysis is conducted.[4] With these trade-offs between the structure effect and energy intensity effect, IDA conducted at a single-level provides decomposition results that are somewhat specific. Much useful information especially that related to structure change at different levels is masked.

3. The multilevel-parallel (M-P) model

Consider a two-level case. Assume that the total energy consumption can be disaggregated into n sectors at level 1, and sector i can be further disaggregated into m_i subsectors at level 2. The total energy consumption at level 0 can be decomposed by the following identity:

$$E^{L0} = \sum_{i=1}^{n}\sum_{j=1}^{m_i} E_{ij}^{L2} = \sum_{i=1}^{n}\sum_{j=1}^{m_i} A^{L0}\frac{A_i^{L1}}{A^{L0}}\frac{A_{ij}^{L2}}{A_i^{L1}}\frac{E_{ij}^{L2}}{A_{ij}^{L2}} = \sum_{i=1}^{n}\sum_{j=1}^{m_i} A^{L0}S_i^{0,1}S_{ij}^{1,2}I_{ij}^{L2} \tag{5}$$

$$D_{tot}^{L0} = D_{act}^{L0}\cdot D_{str}^{0,1}\cdot D_{str}^{1,2}\cdot D_{int}^{L2} \tag{6}$$

where $S_i^{0,1} = \frac{A_i^{L1}}{A^{L0}}$ is the share of sector i in the overall activity and $S_{ij}^{1,2} = \frac{A_{ij}^{L2}}{A_i^{L1}}$ is the share of subsector j within sector i. Hence $D_{str}^{0,1}$ gives the impact of structure changes at level 1, while $D_{str}^{1,2}$ is the impact of subsector structure change at level 2 within the corresponding sector at level 1. The meanings of other notations are the same as those defined in Section 2. From Eq. (6), the total energy consumption change at level 0 is decomposed to give the

[4] For example, in Sun and Malaska (1998), CO_2 emission changes in developed countries are decomposed. The large structure effects of individual countries offset each other, leading to a marginal structure effect for the entire country group.

impacts of total activity change at level 0, structural change at each disaggregation level, and intensity change at the finest level.

Although the data used are collected at different levels in the energy consumption data hierarchy, the factors in Eq. (6) will be calculated using a procedure the same as in the single-level IDA. The effects obtained are therefore treated independently as illustrated in Fig. 2. Since all the effects appear in parallel, we say that this model has a parallel structure and refer to it as the multilevel-parallel (M-P) model. For an energy data hierarchy with a total of k levels, we have:

$$D_{tot}^{L0} = D_{act}^{L0} \cdot D_{str}^{0,1} \cdot D_{str}^{1,2} \cdots D_{str}^{k\text{-}1,k} \cdot D_{int}^{Lk} \tag{7}$$

where $D_{str}^{k\text{-}1,k}$ is the structure effect within the sub-categories of level k-1, and D_{int}^{Lk} is the energy intensity effect at level k. The M-P model retains the feature of simplicity in computation in a single-level IDA model. This is the multilevel IDA model often used by researchers in the literature. Examples include Li et al. (1990), Gardner (1993), Huang (1993), Alam (2002), Ma and Stern (2008), and Patrick (2013). Interpretations of various structure effects in the M-P model and their practical significance were also reported in some of these studies.

[Figure 2 here]

4. The multilevel-hierarchical (M-H) model

Besides using the parallel structure in a multilevel analysis, we can follow the energy consumption data hierarchy and decompose the aggregate change step-by-step. Using this concept and for the same example in Section 3, we may define the following identities:

$$E^{L0} = \sum_{i=1}^{n} E_i^{L1} = \sum_{i=1}^{n} A^{L0} \frac{A_i^{L1}}{A^{L0}} \frac{E_i^{L1}}{A_i^{L1}} = \sum_{i=1}^{n} A^{L0} S_i^{0,1} I_i^{L1} \tag{8}$$

$$I_i^{L1} = \frac{E_i^{L1}}{A_i^{L1}} = \sum_{j=1}^{m_i} \frac{A_{ij}^{L2}}{A_i^{L1}} \frac{E_{ij}^{L2}}{A_{ij}^{L2}} = \sum_{j=1}^{m_i} S_{ij}^{1,2} I_{ij}^{L2} \tag{9}$$

The total energy consumption at level 0 is thus decomposed hierarchically in two steps as:

$$D_{tot}^{L0} = D_{act}^{L0} \cdot D_{str}^{0,1} \cdot D_{int}^{L1} \tag{10}$$

$$D_{int}^{L1} = D_{str}^{1,2} \cdot D_{int}^{L2} \tag{11}$$

Now the total energy consumption change at level 0 is decomposed at level 1 and the energy intensity effect at level 1 is further decomposed to give the sub-structure effect and the sub-intensity effect at level 2. This leads to a stepwise decomposition procedure and the decomposition model has a hierarchical structure as shown in Fig. 3.

[Figure 3 here]

For a total of k different levels of disaggregation, we have:

$$\begin{aligned} &D_{tot}^{L0} = D_{act}^{L0} \cdot D_{str}^{L1} \cdot D_{int}^{L1} \\ &D_{int}^{L1} = D_{str}^{1,2} \cdot D_{int}^{L2} \\ &\vdots \\ &D_{int}^{L(k-1)} = D_{str}^{k\text{-}1,k} \cdot D_{int}^{Lk} \end{aligned} \tag{12}$$

where $D_{str}^{k-1,k}$ and D_{int}^{Lk} are respectively the sub-structure and intensity (or sub-intensity) effect at level k. The decomposition analysis comprises a series of decomposition steps and each of them uses the data at a specific level in the energy consumption data hierarchy and gives a specific structure effect. Since the effects are generated hierarchically, we say that this model has a hierarchical structure and refer to it as the multilevel-hierarchical (M-H) model.

Theoretically, the M-H model has the following good properties. First, decomposition analysis is conducted hierarchically which is consistent with the energy consumption data hierarchy. Second, since the energy intensity effect obtained at an aggregate level can be further decomposed into sub-effects at a finer level, the relationships between structure effects and intensity effects at different levels can be better understood. Third, using a stepwise decomposition procedure, the M-H model, which allows sectors to be further disaggregated, has the flexibility in handling changes and refinements in the data hierarchy. This property enables an asymmetric hierarchy to be used.

A drawback of the M-H model is that computationally it is more cumbersome than the conventional decomposition procedure used in the single-level model and the M-P model. By decomposing changes more than once, the formulae of sub-effects can be quite complicated. Using the most popular LMDI-I method as an example, the three effects and the two sub-effects in Eqs. (10)-(11) can be estimated as:

$$D_{act}^{L0} = \exp\left(\sum_i \frac{L\left(E_i^T, E_i^0\right)}{L\left(E^T, E^0\right)} \ln\left(\frac{A^T}{A^0} \right) \right) \tag{13}$$

$$D_{str}^{0,1} = \exp\left(\sum_i \frac{L\left(E_i^T, E_i^0\right)}{L\left(E^T, E^0\right)} \ln\left(\frac{A_i^T / A^T}{A_i^0 / A^0} \right) \right) \tag{14}$$

$$D_{int}^{L1} = \exp\left(\sum_i \frac{L\left(E_i^T, E_i^0\right)}{L\left(E^T, E^0\right)} \ln\left(\frac{E_i^T / A_i^T}{E_i^0 / A_i^0} \right) \right) \tag{15}$$

$$D_{str}^{1,2} = \exp\left(\sum_i \frac{L\left(E_i^T, E_i^0\right)}{L\left(E^T, E^0\right)} \left(\sum_j \frac{L\left(E_{ij}^T / A_i^T, E_{ij}^0 / A_i^0\right)}{L\left(E_i^T / A_i^T, E_i^0 / A_i^0\right)} \ln\left(\frac{A_{ij}^T / A_i^T}{A_{ij}^0 / A_i^0} \right) \right) \right) \tag{16}$$

$$D_{int}^{L2} = \exp\left(\sum_i \frac{L\left(E_i^T, E_i^0\right)}{L\left(E^T, E^0\right)} \left(\sum_j \frac{L\left(E_{ij}^T / A_i^T, E_{ij}^0 / A_i^0\right)}{L\left(E_i^T / A_i^T, E_i^0 / A_i^0\right)} \ln\left(\frac{E_{ij}^T / A_{ij}^T}{E_{ij}^0 / A_{ij}^0} \right) \right) \right) \tag{17}$$

It can be seen that the formulae used at the first decomposition level, i.e. Eqs. (13)-(15), are exactly the same as those in a single-level decomposition procedure, while the formulae at the second decomposition level, i.e. Eqs. (16)-(17), are more complicated since an explanatory effect is further decomposed into sub-effects. It can be proved that not all the IDA methods are directly applicable or can be transformed and integrated with the M-H model. Further research indicates that whether or not an IDA method is applicable to the stepwise decomposition procedure will depend on its feasibility for further decomposition to give sub-effects. More discussions on the applicability of various IDA methods in the form of a multilevel decomposition model will be presented in Section 6.

5. Illustrative examples

We compare the single-level, M-P, and M-H models using two examples. Assume a two-level energy data hierarchy where level 1 comprises two sectors and a sector may comprise sub-sectors at level 2. The first example deals with a symmetric hierarchy, i.e. both sectors have subsectors, while the second deals with an asymmetric hierarchy, i.e. only one of the sectors has subsectors.

5.1 Example 1: Symmetric hierarchy

Assume the data in Table 1 where level 1 has two sectors and each has two subsectors at level 2. At level 1, the activity share of Sector 1, the more energy intensive of the two sectors, increases from year 0 to year *T*. At level 2, the activity share of the more energy intensive subsector also increases for both Sector 1 and Sector 2. Energy intensities decrease in all the sectors and subsectors.

[Table 1 here]

The multiplicative LMDI-I method, one of the most popular IDA methods, is adopted to decomposed the data in Table 1.[5] Four decomposition analyses are conducted. The decomposition results of the two single-level decomposition model using respectively the sector level data (level 1) and subsector level data (level 2) are shown in Table 2, while the decomposition results of the two multilevel decomposition models are shown in Table 3.[6] From Table 2 and Table 3, the M-P model and the single-level model (level 2) give the same estimates for the activity effect and the intensity effect, while the product of the two structure effects in the M-P model equals the structure effect of the single-level model (level 2). By using the M-P model, the cancellation issue of the structure effect in the single-level model due to activity shifts within sectors is revealed. The M-P model can therefore be seen as an improvement over the single-level model by distributing the aggregate structure effect into the contribution of detailed sub-structure effects at different levels, i.e. $D_{str}^{0,2} = D_{str}^{0,1} \cdot D_{str}^{1,2}$.

[Table 2-3 here]

Similarly, by comparing the results of the M-H model with those of the single level model (level 1), the two models obtain the same estimates for the activity effect and the sectoral structure effect.[7] The intensity effect at level 1 equals to the product of intensity effect at level 2 and the structure effect within sectors. The M-H model provides a better estimate of energy efficiency improvement arising from reductions in the subsector energy intensities. By using the M-H model, the effect of structure change within sectors is separated from the energy intensity effect that would have been obtained had single-level decomposition (level 1) been adopted, i.e. $D_{int}^{L1} = D_{str}^{1,2} \cdot D_{int}^{L2}$. The M-H model, therefore, can be seen as an improvement over the single-level model by isolating the impacts of activity shifts at the subsector level from the true energy efficiency

[5] For an overview of various commonly used IDA methods, refer to Ang (2004).

[6] Eqs. (13)-(17) are used to obtain the M-H decomposition results. Readers can refer to Ang (2004) for the formulae for the single-level models and the M-P model.

[7] This is to be expected since Eq. (8) is exactly the same as Eq. (1).

improvement. Furthermore, since the product of the sub-structure effect and the intensity effect in the M-H model is the same as the intensity effect of the single-level model (level 1), the linkage among structure effects and that among intensity effects across levels can be established.

5.2 Example 2: Asymmetric hierarchy

Assume that Sector 2 is a single aggregate, i.e. there is no subsector in Sector 2. The dataset would be the same as that shown in Table 1 except that the last two rows are removed. Decomposition analysis is now conducted for an asymmetric hierarchy. Since only the energy consumption data hierarchy at level 2 has changed while level 1 is the same as in Example 1, it is natural to expect identical explanatory effects linked to level 0 and level 1 (i.e. D_{act}^{L0} and $D_{str}^{0,1}$) in these two examples. Table 4 shows the decomposition results given by the multilevel models using the multiplicative LMDI-I method.[8] From the decomposition results, we find that the decomposition results by the M-H model satisfy our expectation. In other words, changes in the energy consumption data hierarchy will only affect relevant effects in the M-H model. In contrast, all the effects given by the M-P model are different when there are changes in the data hierarchy irregardless of the level where the changes occur. In this respect, the M-H model should be preferred when dealing with an asymmetric hierarchy.

[Table 4 here]

6. Issues in implementing multilevel decomposition analysis

We present the methodological and practical issues which are relevant to the adoption of the commonly used IDA methods in multilevel decomposition analysis. In the literature, the properties and features of these IDA methods have been widely discussed. See, for example, Greening et al. (1997), Ang and Zhang (2000), and Ang (2004). These studies are, however, based on single-level decomposition analysis. We now study them in the context of multilevel decomposition analysis.

6.1 Applicability of IDA methods

Since the M-P model is very similar to the conventional single-level model in calculation procedure, the properties and features of all the existing IDA methods in the

[8] To make the M-P model applicable to the asymmetric case, we assume that sector 2 has a dummy subsector with energy consumption and activity output exactly the same as sector 2.

literature are applicable to the M-P model.[9] In the M-H model, the effects are estimated step by step. Whether or not an IDA method is still equally applicable depends on its feasibility for further decomposition to give sub-effects. Our investigation shows that it is directly feasible for multiplicative IDA methods linked to the Divisia index and for additive IDA methods linked to the Laspeyres index. The details and the relevant formulae are given in Appendix A. This also means that additive methods linked to the Divisia index and multiplicative methods linked to the Laspeyres index are not directly feasible. However, they can be readily incorporated within the M-H model framework through simple transformations. In the former, we transform the logarithmic change into the linear change, while in the latter we transform the index from using the arithmetic mean to the geometric mean. Further details are given in Appendix B. In summary and as summarized in Table 5, most popular IDA methods can be directly or indirectly applied in the M-H model framework. An exception is the Fisher ideal index where the formula cannot be transformed to meet the requirements.

[Table 5 here]

6.2 Computational issues

Adopting different decomposition procedures in the multilevel analysis, different decomposition results will be obtained for the M-P model and the M-H model, even though the same IDA method is applied. From Appendix A and Appendix B, we find that for those IDA methods of which the weights add up to unity, estimates of effects not involving further decomposition (e.g. activity effect, structure effect at the first level, etc.) are consistent for both the M-P model and the M-H model. They include the arithmetic mean Divisia index (AMDI) and the general parametric Laspeyres methods. For those effects where further decomposition is performed, nearly all IDA methods except the general parametric Laspeyres methods (e.g. the conventional Laspeyres, Passche, etc.) produce different results. Nevertheless, despite this advantage, the general parametric Laspeyres methods tend to give a large residual term in the decomposition results which limits their applicability. To summarize, most IDA methods, especially the popular ones,

[9] As the number of factors in the IDA identity increases, the computation effort in using the Shapley/Sun method and the generalized Fisher index method can be expected to increase. This applies to the conventional single-level model but the problem is more serious in the case of the M-P model since it tends to have more factors than the single-level model.

will give different results in the parallel decomposition structure used by the M-P model and in the hierarchical decomposition structure used by the M-H model.

By adopting the parallel decomposition structure as in the conventional single-level model, the M-P model is relatively easy to apply. This computational advantage applies to most IDA methods. An exception is the Shapley/Sun method for which the number of terms in the decomposition analysis formulae increases exponentially as the number of factors in the IDA identity increases.[10] By distributing the factors to different levels and calculating them in multiple steps, the M-H model actually reduces the computational effort needed for the Shapley/Sun method.[11] This advantage is even more noticeable when the energy data hierarchy comprises many disaggregation levels and/or there are many factors in the IDA identity.

7. Decomposition of United States and China industrial energy consumption

We now use the M-H model to decompose changes in industrial energy consumption in the United States and China.[12] To be more general and for better illustration, the multiplicative LMDI-I is used in the US study while the additive LMDI-I in the China study. The energy data hierarchy in the US study is as follows: the industrial sector has two broad groups, i.e. manufacturing and non-manufacturing, and manufacturing has 21 NAICS 3-digit subsectors while non-manufacturing is a single sector. The data hierarchy therefore has a two-level asymmetric structure. In the China study, data at both national level and regional level are collected. The energy consumption hierarchy is as follows: the national level industrial energy consumption consists of consumptions in eight geographical regions, and for each region the industrial sector has 27 subsectors. The data hierarchy therefore has a two-level symmetric structure. Further details about the data hierarchies and data are given in Appendix C.

7.1 Decomposition results for the United States

[10] In multilevel decomposition, the number of factors is usually more than four which gives more than 4!=24 computational terms in the decomposition analysis formulae for the Shapley/Sun method. The number increases to 5!=120 when the aggregate energy consumption is decomposed to five factors. That is the reason why Shapley/Sun method is seldom applied in the IDA identity with more than five factors.

[11] For example, if a four-factor M-P decomposition model as Eq. (5) is restructured into a M-H model as Eqs. (8) and (9), the number of computational terms will be reduced from 24 (=4!) to 8 (= 3!+2!).

[12] These two real cases are used to show the practical significance of the M-H model because it is new in the literature. As to the M-P model, the practical significance has been illustrated in many previous studies. For conciseness, we will not present and explain the results given by the M-P model.

Multiplicative LMDI-I and Eqs. (A.5), (A.7) and (A.11) are used to decompose the total US industrial energy consumption changes from 1985 to 2004, i.e. from 16,212 to 17,471 trillion Btu. The results obtained are shown in the bar chart in Fig. 4. The first four bars respectively show the actual percentage change in aggregate energy consumption, and the contributions to this change from three effects at the first level of the hierarchy. Overall activity growth is the main contributor to the increase in energy consumption. The small positive structure effect at this level indicates a small shift in product mix from non-manufacturing to manufacturing. The results also show substantial improvements in energy efficiency at the two-sector level. To proceed further, the energy intensity effect at the industry group level (bar four) is treated as a composite effect of two sub-effects computed at the NAICS 3-digit sector level. These two sub-effects give the impacts of changes in product mix at the 3-digit sector level in manufacturing and changes in 3-digit level energy intensities. Estimates of these two sub-effects are shown in bar five and bar six in Fig. 4.

The advantages of applying the M-H model as shown above are as follows. Contributions of the driving forces at the two disaggregation levels are quantified and the linkages between effects and sub-effects at the two levels are established. The analysis is conducted by taking the non-manufacturing sector into consideration. Since the data for non-manufacturing are given as a single aggregate, one may treat it separately from the manufacturing sector and the asymmetric hierarchy can be applied. The M-H model ensures that any modifications to the classification system at an intermediate level, for example by disaggregating the non-manufacturing sector into subsectors such as agriculture, construction, etc., will not affect the decomposition results obtained at a higher aggregation level.

[Figure 4 here]

7.2 Decomposition results for China

Additive LMDI-I and Eqs. (B.1)-(B.4) are used to decompose industrial energy consumption change from 1997 to 2007 in China, i.e. from 1,060 to 2,383 million tonnes of coal equivalent (Mtce). The decomposition results are summarized in Figs. 5-7. From Fig. 5, total energy consumption increased by 1,323 Mtce. Value added growth contributed to an increase of 2,016 Mtce at the national level. The marginal negative structure effect shows that industry value added of the eight regions grew at fairly consistent rates with the less energy-intensive regions grew slightly faster than the other regions. The energy intensities decreased consistently in all the eight regions, and the results show that without energy intensity improvement the energy consumption in 2007 would have been 658 Mtce higher. The regional energy intensity effect can be further taken as a composite effect of two sub-effects at the sectoral level of the industry hierarchy. The sub-structure effect quantifies the impact of changes in the composition of industry sector of the eight regions and their contributions to the national energy consumption change. The sub-intensity effect captures the impact of energy intensity changes of each of the 27 industrial sectors. From bar five and bar six in Fig. 5, efficiency improvements achieved in various industrial sectors in the eight regions led to a reduction of a total of 737 Mtce in energy consumption, which is higher than the 658 Mtce estimated at the higher aggregation level. The difference between the two estimates is due to sector shifts within the industry in the eight regions which is depicted in bar five. In other words, if the conventional single-level decomposition at the sectoral level was conducted, the sub-structure effect would be cancelled out by the negative regional structure effect and would not be captured.

[Figure 5 here]

Using the M-H model, we can also split the sub-effects as shown in Fig. 5 into the contributions of components at sub-category level. As a result, the differences among the eight regions are revealed. The contributions of the eight regions to the sub-structure effect and the sub-intensity effect are shown in Fig. 6 and Fig. 7 respectively. The results show that almost all the regions experienced activity shifts towards more energy-intensive sectors, especially in the North Coast, Central and Western regions. The only exception is the Northeast region where “transport, storage, postal and telecommunications services” and other non-manufacturing industries developed rapidly (Fig. 6). Energy intensity of industrial subsectors decreased in all the regions and as a result relatively large energy savings were achieved at the national level (Fig. 7).

[Figure 6-7 here]

8. Discussion and conclusions

We discuss the limitations of single-level decomposition in IDA applied to energy and study how multilevel analysis can help to address these limitations. We introduce two multilevel decomposition models, the M-P model and the M-H model, and study their features. The M-P model, the multilevel decomposition model often used by researchers in the IDA literature, adopts the same calculation procedure as conventional single-level model. In contrast, the M-H model adopts a stepwise decomposition procedure which is totally new in the IDA literature. To extend from single-level to multilevel analysis using the M-H model, modifications via transformations are needed to some popular IDA methods. We further discuss the practical significance of the M-H model and present real cases to illustrate.

A pertinent question that arises is that if multilevel data are available, which of the two multilevel models, the M-P or the M-H, is preferred. A direct answer to this question is that it depends on the study objective and/or the analyst's own preference. From the discussion in this paper, if the energy consumption data hierarchy is symmetric, both models can be seen as improvements to the conventional single-level IDA models, while if the data hierarchy is asymmetric, the M-H model is recommended. The M-P model is easier to apply regarding the effect estimation for most IDA methods. If the objective is to conduct the multilevel analysis with less computational effort, the M-P model shall be preferred. An exception is the Shapley/Sun method where the stepwise procedure used by the M-H model will help reducing the computational effort.

The main difference between the two multilevel decomposition models is the decomposition procedure adopted. With a parallel decomposition structure, the numerical results given by the M-P model are sensitive to changes in the data hierarchy. Even changes at a fine level can affect the results of the explanatory factors defined at the aggregate level. The hierarchical decomposition structure used by the M-H model, on the contrary, can provide consistent decomposition results and changes in the data hierarchy will only affect the results of the explanatory factors defined at relevant levels. Further discussion on these two decomposition structures and the causes of their differences are needed to clarify the preference of these two multilevel models. These are possible research areas for further study.

The use of multilevel decomposition model will help to improve result presentation and usability. For example, Fisher-Vanden et al. (2004) decompose China's energy intensity changes at six different levels of industry disaggregation. If the multilevel decomposition model was used, the six sets of results could be integrated into a multilevel decomposition model in a hierarchical manner and be interpreted in a more coherent way. Wu (2012) decomposes aggregate energy intensity of China at both the national level and regional level, and investigates the drivers of changes at these two levels. Similarly, if the multilevel decomposition model was applied, valuable information about industrial relocation in the country would be revealed. Besides industry, multilevel decomposition analysis could also be fruitfully applied to other sectors of energy use when sector classification is more than one level or complicated. Examples of such studies are Mairet and Decellas (2009) for the service sector, Papagiannaki and Diakoulaki (2009) for passenger transport, and Hojjati and Wade (2012) for the household sector. It is also possible to incorporate the multilevel decomposition model to track economy-wide energy efficiency trends where currently the single-level decomposition model is the norm for studies conducted by most countries and international organizations.

Application of the multilevel decomposition model is not limited to obtaining the hierarchical structure effects studied in this paper. It is actually a general decomposition technique that can be applied to decompose any aggregate with multiple disaggregation levels. For example, it can be used to study the impact of fuel mix change and factors contributing to changes in energy-related greenhouse gas emissions. Examples for such studies where it can be applied are Steenhof (2006), Lescaroux (2008), and Hammond and Norman (2012). In addition, analysts have recognized the need to investigate emissions from electricity consumption using a two-stage analysis. See, for example, Nag and Kulshreshtha (2000) and Lu et al. (2012). Electricity as an energy source is at the same time a product of energy service. With this special property, its emission coefficient in IDA can be further decomposed to give effects linked to electricity generation.[13] This is an application that can be achieved by using the stepwise property of the M-H model.

[13] See Steenhof and Weber (2011) for an example of explanatory effects linked to electricity generation.

Appendix A. General formulae of the M-H model

Assume that V is an aggregate to be decomposed into k components and each is a function of n factors, i.e. $V = \sum_{i=1}^{k} V_i = \sum_{i=1}^{k} X_{1,i} X_{2,i} \cdots X_{n,i}$. Further assume that factor n in the i component is a function of r sub-components with m sub-factors, i.e. $X_{n,i} = \sum_{j=1}^{r} X_{n,ij} = \sum_{j=1}^{r} x_{1,ij} x_{2,ij} \cdots x_{m,ij}$. From period 0 to period T the aggregate changes from V^0 to V^T and factor n changes from $X_{n,i}^{0}$ to $X_{n,i}^{T}$, where i=1…k. We then have the identities (A.1) to (A.2) for multiplicative decomposition and (A.3) to (A.4) for additive decomposition:

$$D_{tot} = V^T / V^0 = D_{X_1} D_{X_2} \cdots D_{X_n} D_{rsd} \tag{A.1}$$

$$X_{n,i}^{T} / X_{n,i}^{0} = D'_{x_1} D'_{x_2} \cdots D'_{x_m} D'_{rsd} \tag{A.2}$$

$$\Delta V_{tot} = V^T - V^0 = \Delta V_{X_1} + \Delta V_{X_2} + \cdots + \Delta V_{X_n} + \Delta V_{rsd} \tag{A.3}$$

$$X_{n,i}^{T} - X_{n,i}^{0} = \Delta V'_{x_1} + \Delta V'_{x_2} + \cdots + \Delta V'_{x_m} + \Delta V'_{rsd} \tag{A.4}$$

where D_{rsd} and ΔV_{rsd} are residual terms.

The general formulae of effect n for multiplicative Divisia index methods are:

$$D_{X_n} = \exp\left(\sum_{i=1}^{k} \omega_i \ln\left(X_{n,i}^{T} / X_{n,i}^{0} \right) \right) \tag{A.5}$$

Putting Eq. (A.2) into Eq. (A.5) we have

$$D_{X_n} = \exp\left(\sum_{i=1}^{k} \omega_i \ln\left(D'_{x_1} D'_{x_2} \cdots D'_{x_m} D'_{rsd} \right) \right) = D_{x_1} D_{x_2} \cdots D_{x_m} D_{rsd}$$

(A.6)

where

$$D_{x_m} = \exp\left(\sum_{i=1}^{k} \omega_i \ln D'_{x_m} \right) = \exp\left(\sum_{i=1}^{k} \omega_i \left(\sum_{j=1}^{r} \varpi_{ij} \ln\left(x_{m,ij}^{T} / x_{m,ij}^{0} \right) \right) \right) \tag{A.7}$$

is the sub-effect m of effect n, and ω_i and ϖ_{ij} are method-specific weight functions of Divisia index methods.

Similarly, the general formulae of effect n for additive Laspeyres index methods are:

$$\Delta V_{X_n} = \sum_{i=1}^{k} s_{n,i}\left(X_{n,i}^{T} - X_{n,i}^{0}\right) \tag{A.8}$$

Putting Eq. (A.4) into Eq. (A.8) we have

$$\begin{aligned}\Delta V_{X_n} &= \sum_{i=1}^{k} s_{n,i}\left(\Delta V'_{x_1} + \Delta V'_{x_2} + \cdots + \Delta V'_{x_m} + \Delta V'_{rsd}\right)\\ &= \Delta V_{x_1} + \Delta V_{x_2} + \cdots + \Delta V_{x_m} + \Delta V_{rsd}\end{aligned} \tag{A.9}$$

where

$$\Delta V_{x_m} = \sum_{i=1}^{k} s_{n,i}\Delta V'_{x_m} = \sum_{i=1}^{k} s_{n,i}\left(\sum_{j=1}^{r} \tilde{s}_{m,ij}\left(x_{m,ij}^{T} - x_{m,ij}^{0}\right)\right) \tag{A.10}$$

is the sub-effect m of effect n, and $s_{n,i}$ and $\tilde{s}_{m,ij}$ are method-specific weight functions of Laspeyres index methods.

The weight functions for the methods in Table 4 are as follows:

A.1. Log mean Divisia index method I (LMDI-I)

$$\omega_i = \frac{L(V_i^T, V_i^0)}{L(V^T, V^0)},\ \varpi_{ij} = \frac{L(X_{n,ij}^{T}, X_{n,ij}^{0})}{L(X_{n,i}^{T}, X_{n,i}^{0})} \tag{A.11}$$

where function $L(a,b) = \dfrac{a-b}{\ln a - \ln b}$ is the logarithmic mean weights.

A.2. Log mean Divisia index method II (LMDI-II)

$$\omega_i = \frac{L(V_i^T, V_i^0)}{\sum_i L(V_i^T, V_i^0)},\ \varpi_{ij} = \frac{L(X_{n,ij}^{T}, X_{n,ij}^{0})}{\sum_j L(X_{n,ij}^{T}, X_{n,ij}^{0})} \tag{A.12}$$

A.3. Arithmetic mean Divisia index method (AMDI)

$$\omega_i = \frac{1}{2}\times\left(\frac{V_i^T}{V^T} + \frac{V_i^0}{V^0}\right),\ \varpi_{ij} = \frac{1}{2}\times\left(\frac{X_{n,ij}^{T}}{X_{n,i}^{T}} + \frac{X_{n,ij}^{0}}{X_{n,i}^{0}}\right) \tag{A.13}$$

A.4. General parametric Laspeyres method

$$s_{n,i} = \frac{V_i^0}{X_{n,i}^0} + \alpha_i \left(\frac{V_i^T}{X_{n,i}^T} - \frac{V_i^0}{X_{n,i}^0} \right), \ \tilde{s}_{m,ij} = \frac{X_{n,i}^0}{x_{m,ij}^0} + \beta_i \left(\frac{X_{n,i}^T}{x_{m,ij}^T} - \frac{X_{n,i}^0}{x_{m,ij}^0} \right) \tag{A.14}$$

where $0 \le \alpha_i \le 1,\ 0 \le \beta_i \le 1$.

A.5. Shapley/Sun method

The general formula for the Shapley/Sun method is relatively complicated. Interested readers can refer to Sun (1998). For the two-factor and three-factor cases, the formulae for the weights are:

Two-factor:

$$s_{n,i} = \frac{V_i^0}{X_{n,i}^0} + \frac{1}{2} \left(\frac{V_i^T}{X_{n,i}^T} - \frac{V_i^0}{X_{n,i}^0} \right)$$

$$\tilde{s}_{m,ij} = \frac{X_{n,i}^0}{x_{m,ij}^0} + \frac{1}{2} \left(\frac{X_{n,i}^T}{x_{m,ij}^T} - \frac{X_{n,i}^0}{x_{m,ij}^0} \right) \tag{A.15}$$

Three-factor:

$$s_{n,i} = \frac{V_i^0}{X_{n,i}^0} + \frac{1}{2} \sum_{\substack{\zeta \in Z \\ \zeta \ne n}} \frac{V_i^0}{X_{n,i}^0 X_{\zeta,i}^0} \Delta X_{\zeta,i} + \frac{1}{3} \prod_{\zeta \in Z} \Delta X_{\zeta,i}$$

$$\tilde{s}_{m,ij} = \frac{X_{n,i}^0}{x_{m,ij}^0} + \frac{1}{2} \sum_{\substack{\zeta \in Z \\ \zeta \ne n}} \frac{X_{n,i}^0}{x_{m,ij}^0 x_{\zeta,ij}^0} \Delta x_{\zeta,ij} + \frac{1}{3} \prod_{\zeta \in Z} \Delta x_{\zeta,ij} \tag{A.16}$$

where $\Delta X_{\zeta,i} = X_{\zeta,i}^T - X_{\zeta,i}^0$, $\Delta x_{\zeta,ij} = x_{\zeta,ij}^T - x_{\zeta,ij}^0$.

Appendix B. Incorporating selected IDA methods in the M-H model

This appendix shows the transformations needed for additive IDA methods linked to the Divisia index and multiplicative methods linked to the Laspeyres index so that they can be incorporated in the M-H model framework.

B.1. Additive methods linked to Divisia index

Using the notations in Appendix A, we have the general formulae of effect *n* for additive methods linked to the Divisia index:

$$\Delta V_{X_n} = \sum_{i=1}^{k} \omega_i \ln\left(X_{n,i}^T / X_{n,i}^0\right) \tag{B.1}$$

The logarithmic change can be transformed as follows into a linear change:

$$\Delta V_{X_n} = \sum_{i=1}^{k} \frac{\omega_i}{L\left(X_{n,i}^T, X_{n,i}^0\right)} \left(X_{n,i}^T - X_{n,i}^0\right) \tag{B.2}$$

Putting Eq. (A.4) into Eq. (B.2) we have

$$\begin{aligned} \Delta V_{X_n} &= \sum_{i=1}^{k} \frac{\omega_i}{L\left(X_{n,i}^T, X_{n,i}^0\right)} \left(\Delta V'_{x_1} + \Delta V'_{x_2} + \cdots + \Delta V'_{x_m} + \Delta V'_{rsd}\right) \\ &= \Delta V_{x_1} + \Delta V_{x_2} + \cdots + \Delta V_{x_m} + \Delta V_{rsd} \end{aligned} \tag{B.3}$$

where

$$\Delta V_{x_m} = \sum_{i=1}^{k} \frac{\omega_i}{L\left(X_{n,i}^T, X_{n,i}^0\right)} \Delta V'_{x_m} = \sum_{i=1}^{k} \frac{\omega_i}{L\left(X_{n,i}^T, X_{n,i}^0\right)} \left(\sum_{j=1}^{r} \varpi_{ij} \ln\left(x_{m,ij}^T / x_{m,ij}^0\right) \right) \tag{B.4}$$

is the sub-effect *m* of effect *n*, and ω_i and ϖ_{ij} are the method-specific weight functions of Divisia index methods.

B.2. Multiplicative methods linked to Laspeyres index

We first transform the arithmetic mean index into a geometric mean index. Assume an arithmetic mean index and its relevant form in a geometric mean index as shown in Eqs. (B.5) and (B.6) respectively:

$$D_{X_n} = \sum_{i=1}^{k} \bar{s}_{n,i} \frac{X_{n,i}^T}{X_{n,i}^0}$$

(B.5)

and

$$\ln D_{X_n} = \sum_{i=1}^{k} \sigma_{n,i} \ln\left(X_{n,i}^T / X_{n,i}^0\right) \tag{B.6}$$

According to Reinsdorf (1996) and Balk (2008), there exists the following relationship for the weights of the arithmetic mean index and its corresponding geometric mean index:

$$\sigma_{n,i} = \bar{s}_{n,i} L\left(D_{X_n}, X_{n,i}^T / X_{n,i}^0\right) \tag{B.7}$$

where $\bar{s}_{n,i}$ is the weight function of an arithmetic mean index and $\sigma_{n,i}$ is the weight function of the corresponding geometric mean index. Putting Eqs. (A.2) into Eq. (B.6), we have

$$D_{X_n} = \exp\left(\sum_{i=1}^{k} \sigma_{n,i} \ln\left(D'_{x_1} D'_{x_2} \cdots D'_{x_m} D'_{rsd}\right)\right) = D_{x_1} D_{x_2} \cdots D_{x_m} D_{rsd} \tag{B.8}$$

where

$$D_{x_m} = \exp\left(\sum_{i=1}^{k} \sigma_{n,i} \ln\left(D'_{x_m}\right)\right) = \exp\left(\sum_{i=1}^{k} \sigma_{n,i} \ln \sum_{j=1}^{r} \bar{s}_{m,ij} \left(x_{m,ij}^T / x_{m,ij}^0\right)\right) \tag{B.9}$$

is the sub-effect *m* of effect *n*. In Eq. (B.9), $\bar{s}_{m,ij}$ is the weight function of the corresponding multiplicative Laspeyres method, and $\sigma_{n,i}$ can be obtained from Eq. (B.7).

Appendix C. Supporting information for the United States and China cases

Based on the EERE (2012) database, the hierarchy of the United States energy consumption data classification system begins with the economy-wide measures of activity and energy intensity. The next level is defined by the broad end-use sectors covered by the Energy Information Administration energy data, i.e. industrial, residential, commercial, and transportation sectors. The industrial sector is comprised of two industry groups, manufacturing and non-manufacturing. The manufacturing sector is made up of 21 NAICS 3-digit sectors, while non-manufacturing is a single aggregate which includes agriculture, forestry and fisheries, mining, and construction. The activity and energy consumption data, as shown in Table C.1, are collected from the EERE database. Value added data in 2000 US dollars are used as the activity indicator and the energy consumption data refer to delivered energy.

Table C.1. Energy consumption (trillion Btu) and value added (billion USD in 2000 price) in the US industry sector, 1985 and 2004

	1985		2004	
	Energy consumption	Value added	Energy consumption	Value added
Industry total	16,211.7	1,612.09	17,470.7	2,357.99
Manufacturing	11,817.1	982.61	15,556.2	1,506.80
Food manufacturing / beverage and tobacco product manufacturing	996.77	141.728	1136.9	155.806
Textile mills / textile product mills	242.14	19.197	231.3	23.214
Apparel manufacturing /leather and allied product manufacturing	48.88	28.948	31.6	19.714
Wood product manufacturing	379.96	28.355	490.7	32.38
Paper manufacturing	2223.79	52.47	2582.9	53.466
Printing and related support activities	71.78	43.23	100.4	44.445
Petroleum and coal products manufacturing	1810.86	24.567	3582.7	24.691
Chemical manufacturing	2194.15	101.065	2950.7	173.559
Plastics and rubber products manufacturing	219.65	32.487	376.9	70.791
Nonmetallic mineral product manufacturing	902.95	29.143	992.5	48.999
Primary metal manufacturing	1467.25	34.145	1736.6	46.471
Fabricated metal product manufacturing	321.49	85.72	343.8	110.742
Machinery manufacturing	215.60	95.12	170.6	100.732
Computer and electronic product manufacturing	157.15	9.041	146.8	260.286
Electrical equipment, appliance, and component manufacturing	109.33	39.633	156.6	49.285
Transportation equipment manufacturing	345.75	162.996	387	194.89
Furniture and related product manufacturing	50.61	25.503	67.7	30.993
Miscellaneous manufacturing	59.00	29.263	70.4	66.337
Non-manufacturing	4,394.6	629.48	1,914.6	851.19

For China, the 1997 and 2007 energy consumption and value added data are collected for eight geographical regions. The industrial sector has 27 subsectors for each region. The data set therefore has a two-level hierarchy. Table C.2 shows the provinces and municipalities in each region and the energy consumption and value added in 2007.[14] The national level energy consumption and value added of the 27 industry subsectors in 2007 are shown in Table C.3. The energy consumption data are collected from NBS (2000, 2008a) and given in million tonnes of coal equivalent (Mtce). According to the data source, primary energy use in electricity generation is distributed to the 27 sectors according to final electricity consumption. The value added data at the regional level are calculated from the regional input-output tables in IDE (2003) and NBS (2008b, 2008c, 2009, 2010).[15] The price indices in NBS (1998-2008) are used to deflate the 1997 data and 2007 data to 2002 prices.

Table C.2. The eight regions and their respective 2007 energy consumption (Mtce), value added (billion RMB in 2002 prices) and energy intensity (tce/million RMB in 2002 prices)

Region	Provinces and municipalities	Energy consumption	Value added	Energy Intensity
Northeast	Heilongjiang, Jilin, Liaoning	229.43	1,787.3	128.37
Northern Municipalities	Beijing, Tianjin	85.46	1,214.6	70.36
North Coast	Hebei, Shandong	409.91	3,056.3	134.12
Central Coast	Jiangsu, Shanghai, Zhejiang	377.67	4,735.3	79.76
South Coast	Fujian, Guangdong, Hainan	246.97	3,506.0	70.44
Central	Shanxi, Henan, Anhui, Hubei, Hunan, Jiangxi	523.14	4,115.5	127.11
Northwest	Inner-Mongolia, Shaanxi, Ningxia, Gansu, Qinghai, Xinjiang	245.23	1,484.2	165.23
Southwest	Sichuan, Chongqing, Yunnan, Guizhou, Guangxi, Tibet	264.85	2,282.0	116.06

[14] The region classification is the same as that in Su and Ang (2010).
[15] The RAS method proposed in Su et al. (2010) is applied in data process.

Table C.3. Industry sectors and the 2007 energy consumption (Mtce) and value added (billion RMB in 2002 prices) by sector

Sector	Energy consumption	Value added
1. Agriculture	78.45	1,996.2
2. Coal mining and processing	67.88	272.0
3. Crude petroleum and natural gas products	29.68	247.4
4. Metal ore mining	14.29	108.5
5. Non-ferrous mineral mining	20.69	123.2
6. Manufacture of food product and tobacco processing	51.90	849.5
7. Textile goods	66.31	447.5
8. Wearing apparel, leather, furs, down and related products	11.49	388.0
9. Sawmills and furniture	10.71	242.0
10. Paper and products, printing and record medium	41.94	348.5
11. Petroleum processing and coking	123.46	198.7
12. Chemicals	325.92	1,037.8
13. Non-metal mineral products	226.34	588.5
14. Metals smelting and pressing	611.92	747.6
15. Metal products	30.60	317.2
16. Machinery and equipment	42.67	858.6
17. Transport equipment	25.06	678.3
18. Electric equipment and machinery	16.46	396.8
19. Electric and telecommunication equipment	20.78	851.7
20. Instrument, meters, cultural and office machinery	2.78	111.3
21. Other manufacturing products	14.31	385.5
22. Electricity, steam and hot water production and supply	122.31	779.1
23. Gas and water production and supply	13.05	61.2
24. Construction	34.52	1,248.2
25. Transport, storage, postal & telecom. service	220.76	1,991.3
26. Wholesale, retail trade and catering service	70.67	1,769.8
27. Other services	87.70	5,136.8

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Tables

Table 1. Multilevel decomposition: an illustrative example (arbitrary units).

		Year 0				Year T			
Sector/subsector	Level	E_0	A_0	S_0	I_0	E_T	A_T	S_T	I_T
Total	0	50	50	1.0	1.0	64	80	1.0	0.8
Sector 1	1	(30)	(10)	(0.2)	(3.0)	(40)	(20)	(0.25)	(2.0)
Subsector 1	2	20	5	0.1	4.0	30	12	0.15	2.5
Subsector 2	2	10	5	0.1	2.0	10	8	0.1	1.3
Sector 2	1	(20)	(40)	(0.8)	(0.5)	(24)	(60)	(0.75)	(0.4)
Subsector 3	2	8	10	0.2	0.8	15	30	0.375	0.5
Subsector 4	2	12	30	0.6	0.4	9	30	0.375	0.3

Source: The data are taken from an example in Ang (1995). The data enclosed in brackets give the sector level totals.

Table 2. Single level LMDI-I decomposition results: symmetric hierarchy and D_{tot} =1.28

Single level models	D_{act}	D_{str}	D_{int}
Single level decomposition (level 1)	1.5998	1.1183	0.7154
Single level decomposition (level 2)	1.5936	1.2378	0.6489

Table 3. Multiplicative LMDI-I decomposition results: symmetric hierarchy and D_{tot} =1.28

Multilevel models	D_{act}^{L0}	$D_{str}^{0,1}$	$D_{str}^{1,2}$	D_{int}^{L2}
M-P decomposition	1.5936	1.1183	1.1068	0.6489
M-H decomposition	1.5998	1.1183	1.1019	0.6493

Table 4. Multiplicative LMDI-I decomposition results: asymmetric hierarchy and D_{tot} =1.28

	D_{act}^{L0}	$D_{str}^{0,1}$	$D_{str}^{1,2}$	D_{int}^{L2}
M-P decomposition	1.5985	1.1179	1.0407	0.6883
M-H decomposition	1.5998	1.1183	1.0395	0.6883

Table 5. Applicability of popular IDA methods in the M-H model framework

	Additive M-H model	Multiplicative M-H model
Divisia-based methods		
Logarithmic mean Divisia Index (LMDI)	Transformation needed	Directly feasible
Arithmetic mean Divisia Index (AMDI)	Transformation needed	Directly feasible
Laspeyres-based methods		
Laspeyres method	Directly feasible	Transformation needed
Generalized Fisher ideal index	--	Not feasible
Shapley/Sun method	Directly feasible	--

Note: formulae of the directly feasible method can be found in Appendix A, while formulae of methods need transformation are given in Appendix B. LMDI includes LMDI-I method and LMDI-II method

Figures

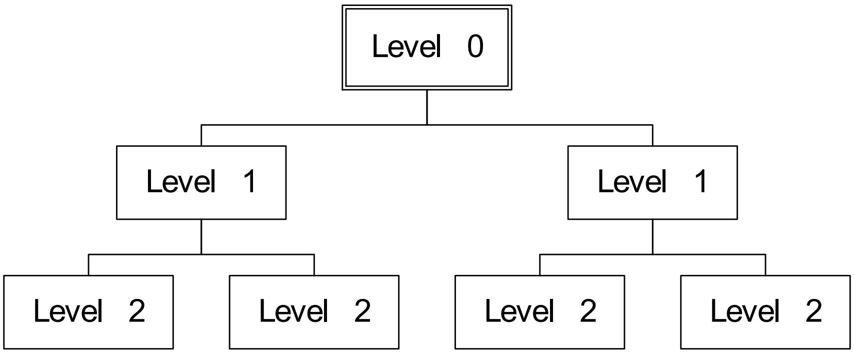

Figure 1. Energy consumption hierarchy

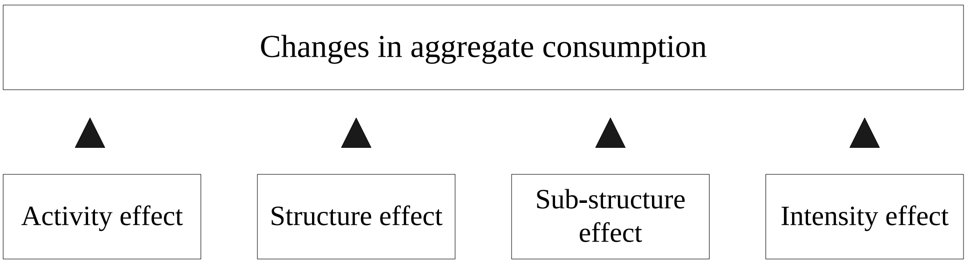

Figure 2. Parallel decomposition structure

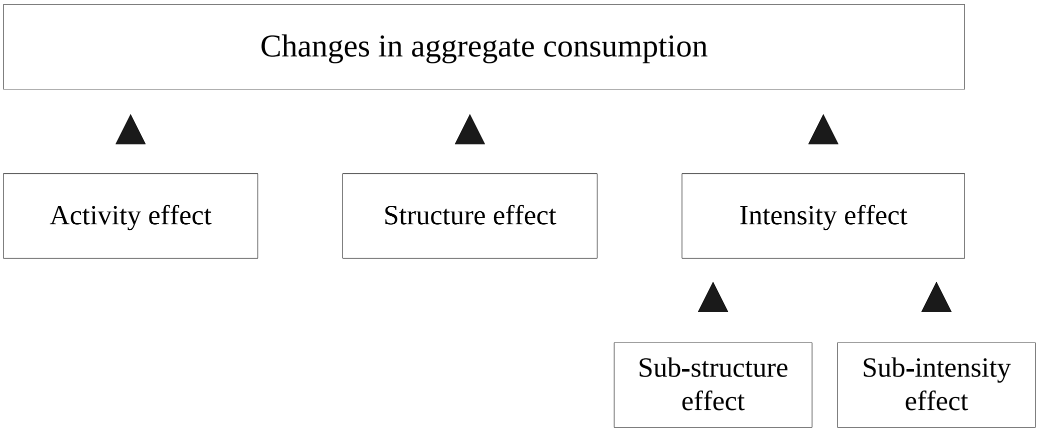

Figure 3. Hierarchical decomposition structure

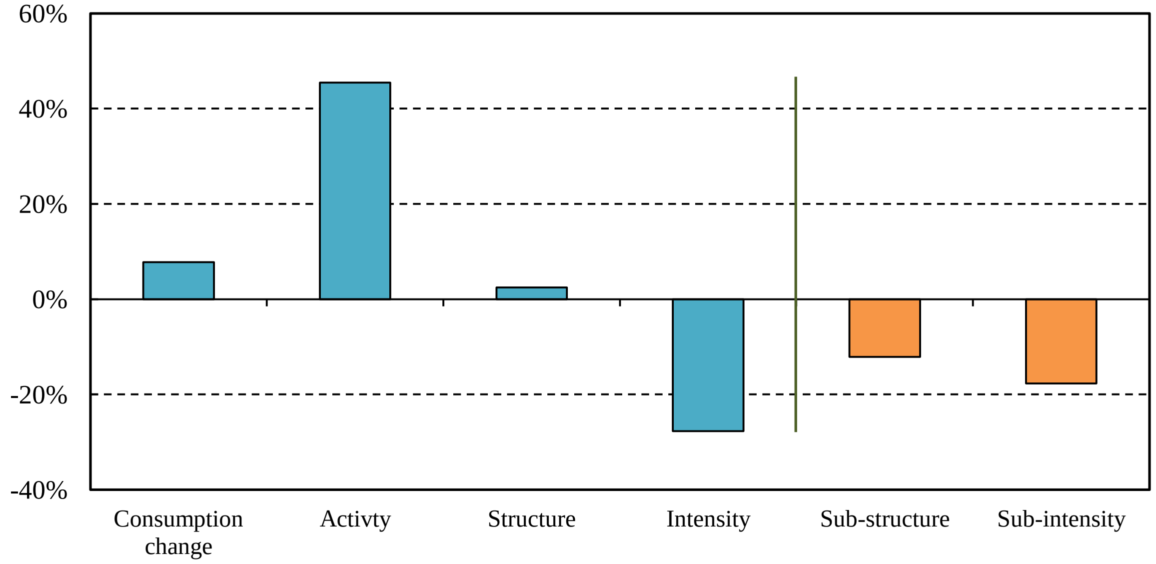

Figure 4. Decomposition results of energy consumption change in US industry hierarchy, 1985-2004

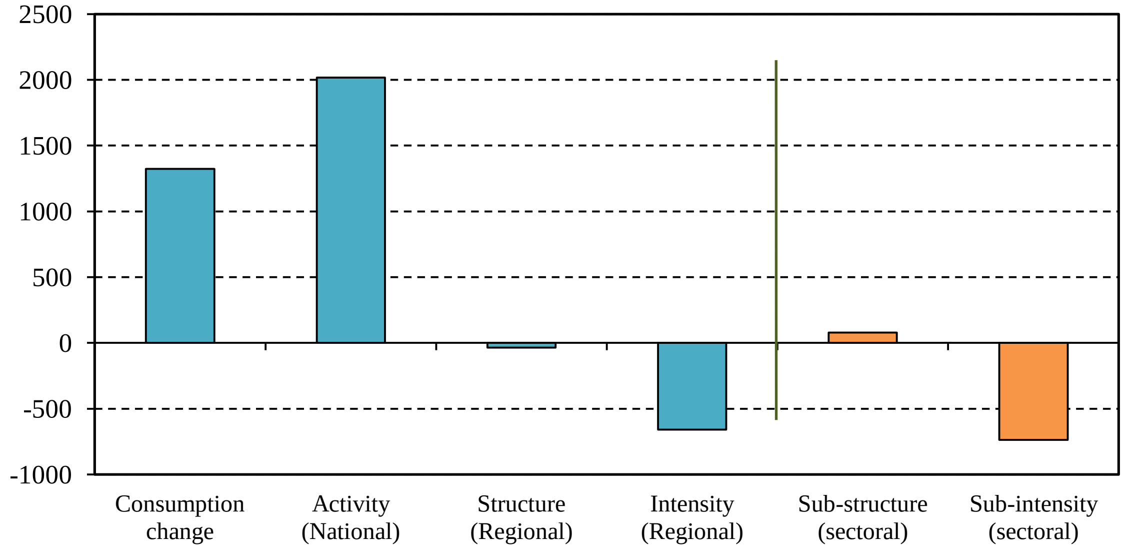

Figure 5. Decomposition results of energy consumption change in China industry (MTce), 1997-2007

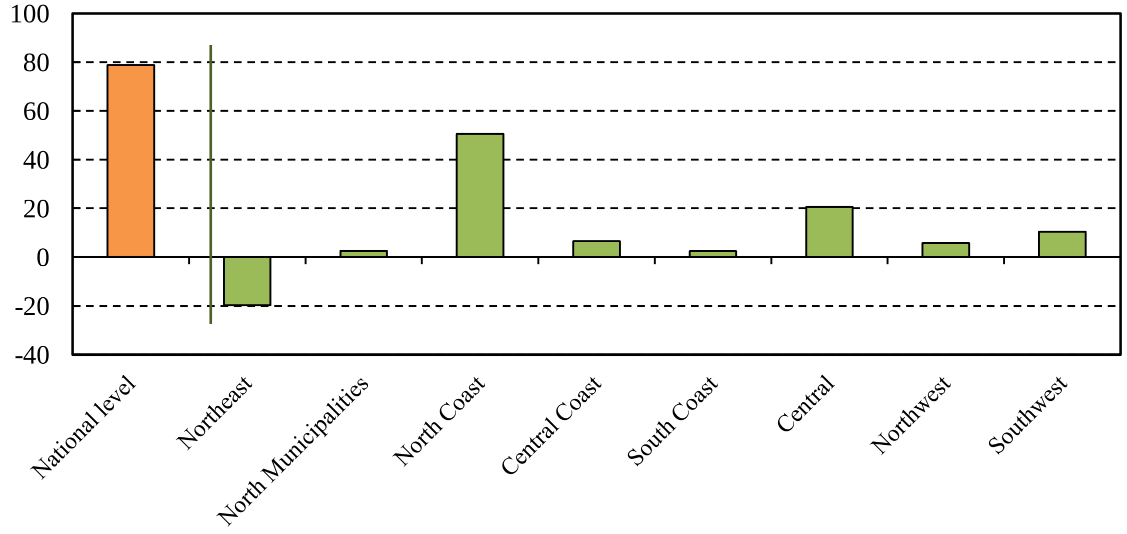

Figure 6. Regional contribution of eight regions in China: Structure effect (MTce)

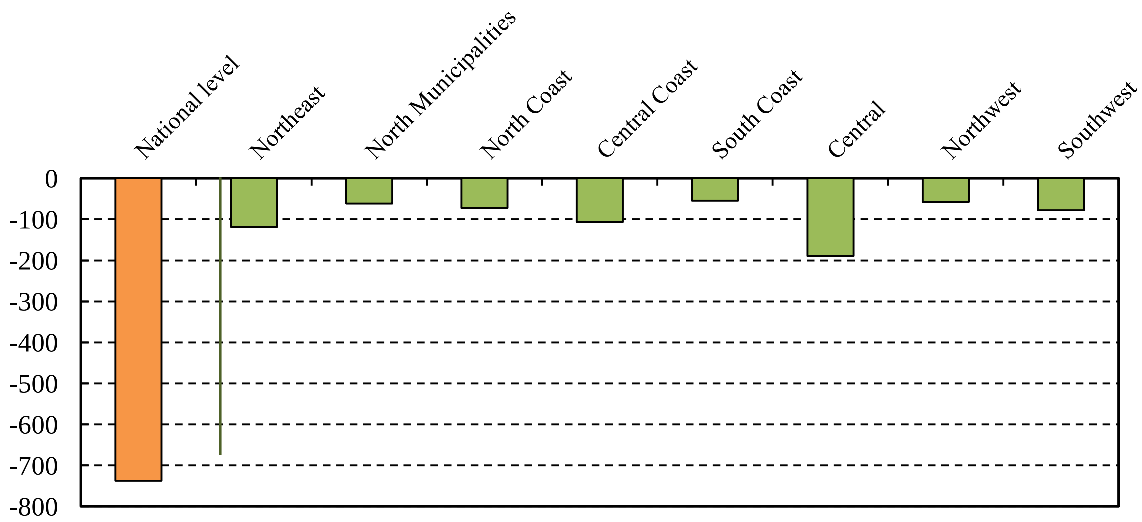

Figure 7. Regional contribution of eight regions in China: Intensity effect (MTce)

Highlights

We discuss the limitations of single-level decomposition in IDA applied to energy and study how multilevel analysis can help to address these limitations.

We introduce two multilevel decomposition models, the M-P model and the M-H model, study their features, and conclude that the latter is the preferred model.

To extend from single-level to multilevel analysis using the M-H model, modifications via simple transformations are needed to some popular IDA methods.

We further discuss the practical significance of the multilevel models and present examples and cases to illustrate.