On the limited usability of the inoperability IO model

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ABSTRACT
This note shows that the inoperability input–output model (IIM) estimates only a part of mainly the negative indirect economic impacts of disasters, whereas it neglects most of the positive indirect impacts. This means that the IIM is not suited to prioritize industries for policy interventions that aim at reducing the negative impacts of such disasters. Besides, this note shows that the application of the IIM is problematic and tends to overestimate the subset of impacts that the model is able to quantify. Finally, we identify two approaches that much better capture the variety of different disaster impacts.

1. Introduction
The original formulation of the inoperability input–output (IO) model (Haimes and Jiang, 2001) was in physical terms and proved very hard to estimate. Its subsequent operationalization in the demand-reduction inoperability IO model (IIM) (Santos and Haimes, 2004) became very popular, in that a series of extensions have been developed and numerous applications have seen the light of day since (see Santos et al., 2014, p. 62, for a brief overview). Greenberg et al. (2012), in fact, claim that the IIM is one of the 10 most important accomplishments in risk analysis of the last 30 years. The early criticism as regards its limitations (Kujawski, 2006) obviously did not stop this proliferation. The reason may be that Kujawski limited his criticism to only questioning the IO assumptions of constant technical coefficients and excess supply, but did not discuss the more fundamental problems of estimating disaster impacts with the IIM. The same will most likely become true for the recent criticism of Dietzenbacher and Miller (2015), who show that the IIM is a straightforward application of the standard IO model ‘with a small tweak’, but do not otherwise criticize the IIM.

The purpose of this note is to investigate which indirect economic impacts may be estimated by means of the IIM and how, and which are ignored. The next section summarizes the complex positive and negative, short-run and long-run, interregional and interindustry economic impacts of major natural and man-made disasters, and indicates that the IIM tries to estimate only a subset of mainly the negative impacts. Section 3 summarizes how
the IIM tries to do that and why it is difficult to do that in a right way, as the predominant character of most disasters, that is, being a supply shock to the economic system, cannot be captured by a demand-driven model like the IIM. Moreover, Section 3 shows that the actual application of the IIM tends to lead to an overestimation of the economic losses that it tries to estimate. The concluding section briefly discusses some alternatives and indicates why only two of them, an established one and a new one, are much better able to capture the complex wider economic impacts of disasters.

2. An overview of the wider economic impacts of disasters

Disasters, such as the tsunami in Japan (2011), lead to both short-run and long-run, and both positive and negative economic impacts. These various impacts occur, not only in the region and the industries directly hit by a disaster, but, due to the disruption of global supply chains, also in seemingly unrelated regions and industries. These wider economic impacts are caused by a series of indirect effects that originate from the direct destruction of production capacity, infrastructure and labour supply in the region at hand. These direct effects, essentially, represent damages to stocks, including human capital, whereas the indirect effects, essentially, represent damages to flows of production and consumption (see Okuyama and Santos, 2014).

First, and foremost, the destruction of production capacity, infrastructure and labour supply will cause a differential disruption in the supply of goods and services by various industries in the region hit by the disaster. In its turn, this drop in supply will have forward or downstream effects on the production of purchasing firms in the same and in other industries, in the same and in other regions. The nature of these forward effects will depend on the replaceability of the inputs at hand.

Second, in case the differential disruption relates to the supply of non-replaceable intermediate (firm to firm) or labour inputs, these wider negative forward effects may be many times larger than the direct supply effect, and may occur not only in the disaster region, but also in industries in faraway regions that depend on these inputs. To estimate the directly related production losses one needs to multiply the drop in the supply of the irreplaceable inputs with the reciprocals of the corresponding technical coefficients, alternatively labelled working-up or processing coefficients (see Oosterhaven, 1988). Some processing coefficients, for example, those for rare metals, may have values that are much, much larger than one, and may thus result in negative forward multiplier effects that are much, much larger than the size of the direct reduction of the supply of the input at hand. The further, second and higher order negative forward impacts can be estimated with an IO-type modelling approach, but this requires an elaborate series of additional, case-specific assumptions (cf. Oosterhaven, 1988; Hallegate, 2008).

Third, in the case of replaceable inputs, other firms will step in to replace these losses and may thus experience positive impacts due to technical and/or spatial substitution effects (see Rose, 2004). Technical substitution occurs when, for example, metal subparts are replaced by plastic subparts, whereas spatial substitution occurs when metal subparts from one origin region are replaced with those from another origin region. Obviously, spatial substitution is far more likely to occur, especially in the short run, than technical substitution, which was the focus of Kujawski’s (2006) critique. The increase in the demand for both types of substitutes will induce the firms supplying them to increase their output, but it
may also induce them to increase their prices, especially if the increase in their own demand for intermediate inputs and labour leads to an increase in the prices of their own intermediate inputs and labour. These secondary demand increases may lead to further positive backward impacts on supplying industries and on the consumption of labour supplying households.

However, even when the downstream industries’ hit are able to fully substitute the loss of the supply of their intermediate and labour inputs, they will most likely have to pay higher prices and wages, which may force them to increase their output prices, with a negative impact on the demand for their own products. When the downstream industries that experience these negative forward impacts are located in the region that is hit, while the industries that produce the replacing inputs are located elsewhere, the result will be an increase in the disaster region’s import coefficients. When the replacements come from the own region, a possible consequence may be a reduction in the exports of the region hit, and a subsequent reduction in the import coefficients of other regions. Moreover, damages to transport infrastructure networks will directly lead to changes in the trading patterns of firms and to spatially differentiated price and spatial substitution effects.

Obviously, the size of all the above effects will depend on the price elasticities of supply and demand, and the elasticities of technical and spatial substitution (Rose and Guha, 2004). None of the above described positive and negative impacts will be picked up by the IIM, as both the technical coefficients and the trade coefficients of that model are assumed to be constant, while prices do not play a role.

Fourth, the destruction of production capacity, infrastructure and labour supply will cause a direct drop in both intermediate demand and final (mainly consumer) demand in the regions hit by the disaster. These direct drops in demand will be due to the fall in the production of their industries and the income of their households. The backward effects of these direct drops in demand will occur in the industries and regions that directly and indirectly supply the industries and households hit by the disaster. Estimating these negative backward impacts is the core competence of the IIM (Santos and Haimes, 2004).

Fifth, terrorist attacks represent a specific type of man-made disasters that hardly cause any of the above described positive and negative effects, as they seldom imply a substantial direct loss of labour, capital or infrastructure. The intended psychological impact of terrorist attacks, however, may be substantial (see Galea et al., 2002). When present, it will lead to a – mainly spatial – redistribution of mainly private consumption demand. The IIM, as any IO model, is well suited to estimate the combined negative and positive backward impacts of this redistribution of consumption expenditures. If less air travel is used and fewer hotels are booked, as in Santos (2006), people and firms will most likely spend the money saved on different items. Note that not only in case of disasters, but for all types of impact studies the analyst should try to make an estimate of the so-called net impacts instead of only the gross impacts (cf. Oosterhaven et al., 2003).

Finally, aside from the wider impacts of the damages to stocks of labour, capital and infrastructure, there will also be short-run and long-run impacts due to private and public reconstruction activities. When these activities relate to the reconstruction of buildings and infrastructure, the positive backward economic impacts will most likely be regionally concentrated. When the reconstruction relates to rebuilding production capacity, the positive backward impacts might well occur in faraway regions, as the capital goods industry is quite specialized. As any IO model, the IIM is well suited to estimate these essentially
long-turn positive backwards impacts. In conjunction, financing these reconstruction programmes, mainly by a mix of higher insurance premiums and higher taxes, will lead to longer run negative forward, spatially spread, macro-economic impacts, which cannot be estimated with the IIM.

Since the IIM is only able to estimate a subset of mainly the negative impacts, while it ignores most of the positive impacts, its use as a risk-management instrument to prioritize support for industry resilience programmes, as first suggested in Santos and Haimes (2004), will most certainly lead to a wrong ranking of industries and thus to wrong policy advice.

3. Problems in the empirical assessment of wider disaster impacts with the IIM

Thus, the ranking of industries only on basis of the impacts that are included in IIM applications is problematic. The IIM literature (e.g. Santos and Haimes, 2004, p. 1447; Lian and Haimes, 2006, pp. 253–254; Santos, 2006, p. 26; Anderson et al., 2007, p. 187), in fact, proposes to estimate two types of rankings of industries; namely one based on the absolute size of the projected economic losses by industry and one based on the relative (i.e. percentage) size of these losses. The latter measure is innovatively labelled as the inoperability of the industry at hand. Both measures are calculated consistently, that is, with exactly the same assumptions of exactly the same standard demand-driven IO model (Leontief, 1951).

Contrary to the IIM literature, I write this model for an open economy (i.e. one with imports and exports) in its most complete structural form, such that the (mostly implicit) assumptions become much clearer than is usually the case. The single region or single nation IO model is then written as:

$$x^r = Z^{rr}i + f^r = Z^{rr}i + f^{rr} + e^r,$$

$$Z^{rr}i = A^{rr}x^r = T^{rr} \otimes A^{•r}x^r,$$

where \(i\) indicates a summation vector with ones, \(•\) a summation over the index concerned, and \(\otimes\) a cell-by-cell matrix multiplication. The economic meaning of 1 and 2 is the following.

For any period \(t\), any region or nation \(r\) and any industry \(i\), Equation 1 indicates that the production/output of its industries, \(x^r_i \in x^r\), follows the demand for its products, which equals the total of that region’s own demand for locally produced intermediate products, \(\sum_j z^{rr}_{ij} \in Z^{rr}i\), plus that region’s final demand, \(f^r_i \in f^r\). The latter, in turn, consists of that region’s own final demand for locally produced products, \(f^{rr}_i \in f^{rr}\), plus the intermediate and final demand from the Rest of the World, that is, exports, \(e^r_i \in e^r\). Economically, the above ‘supply-follows-demand’ assumption implies that the price elasticity of supply is infinite, whereas the price elasticity of demand is zero (see Oosterhaven, 1996, 2012).\(^1\)

For the same \(t\), Equation 2 indicates that local intermediate demand for products from industry \(i\) in region \(r\) is endogenously determined, through unit input coefficients, \(a^{rr}_{ij} \in A^{rr}\), by the output of the local industries \(j\), \(x^r_j \in x^r\). The \(a^{rr}_{ij}\) are usually calculated from a historic IO table by means of \(A^{rr} = Z^{rr}(\hat{x}^r)^{-1}\), where \(\hat{x}\) indicates a diagonal matrix of vector \(x\).

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\(^1\) From this follows that the IO model is an extreme case of a CGE model, which mostly uses finite elasticities for both supply and demand (cf. Rose, 2004).
muchoftheIOandIIMliteraturethese ‘input per unit of output’ coefficients are unjustly called ‘technical coefficients’.

To understand the qualification ‘unjustly’, it is necessary to acknowledge that the \( a_{ij}^{tr} \) are, in fact, the product of a real technical coefficient, \( a_{ij}^{tr} \), and a regional purchase or domestic trade coefficient, \( t_{ij}^{tr} \in T_{rr} \), which indicates the fraction of the total need for intermediate inputs from industry \( i \) from all over the world, \( A^{tr}x^{r} \), that is purchased domestically. Assuming the real technical coefficients to be fixed in time is more or less reasonable, at least for the short run, but assuming the domestic trade coefficients to be fixed is much less reasonable (cf. Oosterhaven and Polenske, 2009). In face of a major disaster, the latter assumption should even be considered highly implausible, as firms will most certainly adjust their regional purchase behaviour if they are confronted with a sudden drop in their usual supply sources of inputs.

Equations 1 and 2 together indicate that final demand has to be exogenously determined outside the IO model, while the production by industry is endogenously determined by the solution of the model, as are all variables that are linked to the production by industry, such as all intermediate inputs, value added, employment and energy use. Dropping all clarifying indices, as usual in the IO and IIM literature, the solution of 1 and 2 is simple:

\[
x = Ax + f \quad \Rightarrow \quad x = (I - A)^{-1}f.
\] (3)

The IIM literature follows the standard IO literature when it takes the difference of 3 between period \( t \) and \( t - 1 \) to calculate the absolute loss of production by industry, \( \Delta x \), due to a disaster at the start of period \( t \):

\[
\Delta x = A \Delta x + \Delta f \quad \Rightarrow \quad \Delta x = (I - A)^{-1} \Delta f.
\] (4)

To this, the IIM adds the normalization of 4 with the lagged output levels, \( x^{-1} \), to get the relative loss of production by industry, \( q = \hat{x}^{-1} \Delta x \), that is, the inoperability by industry:²

\[
q = \hat{x}^{-1}A \Delta x + \hat{x}^{-1} \Delta f \quad \Rightarrow \quad q = (I - \hat{x}^{-1}A \hat{x}^{-1})^{-1}(\hat{x}^{-1} \Delta f) = (I - A^{*})^{-1}c^{*},
\] (5)

where \( (I - A^{*})^{-1} \) is the well-known Ghosh-inverse (Ghosh, 1958). Aside from the implausibility of, especially, the assumption of fixed trade coefficients, applying 4 and 5 to calculate the wider negative backward impacts of a disaster is problematic for several other reasons.

First and foremost, note that a disaster manifests itself, economically, mainly in the form of a direct loss of production capacity, supply of labour and transport facilities, which all represent a supply shock to the economic system, which the demand-driven IO model is incapable to handle. To nevertheless model capacity losses, one might run the IO model with a cap on total output by industry or a cap on trade relations in case of infrastructure losses, but this runs against its very assumptions of, respectively, infinitely elastic supply and fixed trade coefficients. This contradiction can only be solved by a series of case-specific ad hoc assumptions, as in Oosterhaven (1988) or Hallegate (2008).

In the IIM literature, however, the IO model’s inability to accommodate an exogenous change in output levels is circumvented by, mostly implicitly, transforming the production capacity loss into a supposedly equivalent exogenous drop in final demand. However,

² Dietzenbacher and Miller (2015) show that it is far simpler to keep the normalization of (4) at the beginning of (5) instead integrating it in its separate terms. This results in:

\[
q = \hat{x}_{}^{-1}(I - A)^{-1} \Delta f.
\]
transforming the exogenous drop in output into an exogenous final demand drop $\Delta f$ that, with the IO equation 4, projects an endogenous output drop $\Delta x$ that correctly and precisely incorporates the exogenous drop in output is problematic, if not impossible. Take, for instance, the mining industry with almost zero final demand. Even assuming the full loss of this exogenous final demand will not produce an endogenous drop in total mining output that is large enough to incorporate any sizeable exogenous drop in mining output.

When using the IIM equation 5, the problem is even larger, as 5 relates relative changes to each other. In that case, the exogenous percentage drop in production capacity has to be transformed into a percentage drop in exogenous final demand, $\hat{f}^{-1} \Delta f$, that, when downscaled with the final demand to total output ratio, $\hat{x}^{-1} \hat{f}^{-1}$, projects an endogenous percentage drop in output that correctly and precisely incorporates the exogenous drop in output. Unfortunately, nowhere in the IIM literature, one even finds the start of a discussion of this equivalence problem.

In fact, in several applications the opposite happens. When using 5, IIM applications tend to compare the total impacts of uniform reductions of exogenous final demand $c^*$ by industry of, for example, 10% (Santos and Haimes, 2004) or 20% (Barker and Santos, 2010). Alternatively, uniform uncertainty distributions are applied to all industries (e.g. with an average of 35%, as in Barker and Haimes, 2009). Applying a uniform $c^*$ can only be based on the implicit, and sometimes even explicit, but incorrect assumption that $c^*$ has a uniform upper limit of 1. Santos and Haimes (2004, p. 1442) and Equation 5, however, clearly show that $c^* \leq \hat{x}^{-1} f$. This means that $c^*$ has upper limits that equal the industry-specific final demand shares in total output. Ignoring these non-uniform upper limits has two consequences.

First, applying a uniform $c^*$ suggests to the potential user that the resulting ranking of industries is neutral for risk policy purposes, but it is not. A 50% reduction of the exogenous final demand $f$ for the public transport, which has a large upper limit for $c^*$, will result in a much larger inoperability in other sectors than a 50% reduction of $f$ in case of mining products, which has a small upper limit for $c^*$. I have not found any discussion of this problem in the IIM literature, let alone a solution. This strengthens the earlier conclusion that the IIM should not be used to prioritize industries for risk policy purposes.

Second, ignoring the upper limits for $c^*$ leads to a systematic overestimation of the backward inoperability. Take, for instance, the simple case when the average of the output multipliers, $i'(I - A^*)^{-1}$, is 2.0. Then, setting $c^* = 1.0$, in case the production capacity of all industries is totally destroyed, leads to an impossible macro-economic inoperability of $-200\%$, while setting $c^* = 0.5$ if the production capacity of all industries is halved leads to a macro inoperability of $-100\%$, instead of $-50\%$. The reason for this systematic overestimation is the double counting of the endogenous drop in intermediate demand in the exogenous drop in $c^*$, if the exogenous drop in output is not downscaled correctly. This problem is even more prominent if the IO model is closed with regard to household consumption, as in Santos and Haimes (2004), since the multipliers of the extended model are substantially larger, while the exogenous final demand ratios of the extended model are substantially smaller than those of the standard model (see Oosterhaven and Hewings, 2014).

3 For the explicit statement see Santos et al. (2014, p. 63), where it is stated that $c^*$, similar to the inoperability metric $q$, is normalized to perturbation values between 0 and 1.
In sum, correctly using the IIM is difficult; even to only estimate the backward demand effects of a disaster. This second conclusion holds not just for the IIM, but also for the IO model at large (see Oosterhaven and Bouwmeester, 2016). The main reason is that exogenous final demand is the driving force in the demand-driven IO model, while the nature of most disasters is that they generate a shock to the supply-side of the economy.

4. Alternative approaches to capture the wider economic impacts

Unfortunately, the alternative of using the supply-driven version of the IO model (Ghosh, 1958) to add an estimate of the forward impacts to the backward impacts estimated with the demand-driven model is even more problematic. First, because both versions are fundamentally at odds with one another, implying that if the one version is a good representation of reality, by definition, the other version is not (Oosterhaven, 1996). Only a sophisticated case-specific combination of both models may provide a solution (see Oosterhaven, 1988, for the basic idea; and Rose and Wei, 2013, for a recent extensive application).

The second reason is that the supply-driven IO model, even when used alone, is extremely implausible in that it assumes a single homogeneous input with zero supply elasticities and infinitely large demand elasticities, which implies that cars may drive without gasoline and factories may work without labour (see Oosterhaven, 2012, for a recent account). This negative conclusion, of course, also applies to IIM applications of the supply-driven IO model, as in Crowther and Haines (2005).

Ideally, modelling the impacts of natural disasters requires an interregional, interindustry computable general equilibrium (CGE) model, as in Tsuchiya et al. (2007), as CGE models are able to accommodate supply shocks as well as demand shocks, while they take price reactions into account with finite price elasticities instead of the extreme IO and IIM values of either 0 or ∞. Moreover, they often account for technical substitution possibilities, while they almost always account for spatial substitution possibilities.

Unfortunately, different versions of such a model are needed to model short-run impacts as opposed to longer run impacts, because short-run substitution and price elasticities are much closer to zero than their longer run equivalents (Rose and Guha, 2004). Moreover, in longer run simulations, many more variables need to be modelled endogenously. Such time-varying CGE models are complex and rather costly to estimate, even if the essential data, such as interregional social accounting matrices and various elasticities, are available. Note that these problems of using CGE models (see Albala-Bertrand, 2013, for a further discussion) are of a fundamentally different nature compared to the problems of using an IO or IIM model. In the CGE case the problems essentially represent practical problems of implementing the model, whereas in the IO and the IIM case one has to cope with fundamental theoretical problems related to the fact that demand-driven models are unsuitable to model the impacts of supply shocks.

Consequently, the question persists whether the complex problem of estimating the wider impacts of a disaster might not still have a more simple solution instead of the complex CGE solution. At first sight, the hypothetical extraction (HE) method seems to provide a way of simultaneously modelling the downstream, forward impacts, along with the upstream, backward impacts, as applied recently by Muldrow and Robinson (2014)
and as advocated by Dietzenbacher and Miller (2015). The reason for its attractiveness ‘at first sight’ is that the HE method extracts a complete row from the IO matrix, along with a complete column (Paelinck et al., 1965; Strassert, 1968). However, interpreting the extraction of a row of the IO matrix in the demand-driven IO model to represent the forward impacts of the extracted industry is faulty. It only measures the direct impacts of the complete disappearance of the demand for an industry’s intermediate sales. Not even the higher order backward impacts of this disappearance are measured, and definitely not the forward impacts of the secession of these sales upon the purchasing industries.

Recently, Oosterhaven and Bouwmeester (2016) proposed to use a non-linear programming model that combines the simplicity of the IO model with the greater plausibility of the CGE approach, and extensively tested this idea on a hypothetical interregional IO accounting framework. The basic idea of their approach is that both firms and households, in the short run after a disaster, try to stick as much as possible to their old pattern of sales and purchases. They operationalize this idea by minimizing the information gain (Kullback, 1959; Theil, 1967) of a simulated post-disaster interregional IO table compared to the actual pre-disaster table. Recently, this approach has been used to simulate the international impacts of possible Russian natural gas boycotts of different parts of Europe (Bouwmeester and Oosterhaven, forthcoming) and to simulate the interregional impacts of the 2013 floods of the Donau and the Elbe rivers in Germany (Oosterhaven and Többen, forthcoming). Up till now, the outcomes seem plausible. The simplicity of this approach, however, comes at the cost of the absence of a micro-economic foundation other than the assumption that economic actors try to maintain their pre-disaster pattern of economic transactions.

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**References**


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4 Dietzenbacher and Miller (2015) also propose a mixed endogenous/exogenous variant of the dynamic IIM (Lian and Haimes, 2006) and show it to have a monotonic post-disaster recovery path.


