Wider economic impacts of heavy flooding in Germany:

A non-linear programming approach

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Abstract

This paper further develops a new methodology to estimate the wider, indirect impacts of major disasters, and applies it to the 2013 heavy flooding of southern and eastern Germany. We model the attempts of economic actors to continue their usual activities, as closely as possible, by minimizing the information gain between the pre- and post-disaster pattern of economic transactions of the economy at hand. Our findings show that government support of local final demand substantially reduces the indirect losses of the floods, while having a disaster at the top of the business cycle increases them. Moreover, we find that assuming fixed trade origin shares and fixed industry market shares, as in all multi-regional input-output models, leads to implausibly large estimates of the indirect losses.

Keywords: disaster analysis, interregional trade, multi-regional supply-use table, information gain

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1. Introduction

In this paper we investigate the wider, interindustry and interregional impacts of the heavy flooding events of May and June 2013 in Eastern and Southern Germany. Over the past two decades, the use of input-output (IO) models for the assessment of the indirect economic losses caused by man-made or natural disasters gained increasing popularity, as evidenced by two special issues in *Economic Systems Research* and several dozens of papers in scientific journals (cf. Okuyama & Santos 2014). Of these IO model applications, the inoperability IO model (IIM, Santos & Haimes 2004) constitutes the single most used model. An important part of this literature aims at formulating policies to increase the resilience of economic systems, i.e., to reduce the size of the wider impacts of natural or man-made disasters e.g., Anderson et al. 2007, Barker and Santos 2010).

Results from IO applications virtually always show economy-wide losses that are significantly larger than the direct losses of the disaster itself (i.e., the destruction of stocks of infrastructure, capital and labor), as can be observed from the ratios of the economy-wide total losses to the direct losses, i.e., *disaster impact multipliers*. For example, a disaster multiplier of about 2.2 is found for the 2003 blackout in the northwest of the US (Anderson et al. 2007). Santos and Haimes (2004) report results that suggest disaster multipliers due to a 10% drop of demand for air transport because of terrorist attacks varying between 2.5 and 3.6 (the latter including an endogenous workforce), while the ratio of total to direct losses of the attacks on September 11th is estimated to be about 2.0 (Santos 2006).

For the interpretation of these outcomes, it is important to note that the IIM is equivalent to the standard demand-driven IO model expressed in relative changes (Dietzenbacher and Miller 2015). Consequently, the IIM suffers from the same limitations as the standard IO model. These limitations, in this context, in particular, include its rigid assumption of fixed coefficients and its restriction to estimating only the backward, demand-driven impacts of changes in exogenous final demand (Oosterhaven and Polenske 2009).

Natural and man-made disasters, however, cause shocks to both the demand side and the supply side of the economies at hand. The impacts of negative demand shocks may, in principle, be estimated by means of the standard IO model, since both consumers and producers will most likely react by proportionally reducing all their purchases, i.e., by using fixed ratios. Still, the use of the IO model, even to estimate those impacts, is not without problems (Oosterhaven 2017). Especially, double counting impacts needs to be avoided (see also Rose 2004), as disasters cause exogenous shocks to total output and labour income, both of which are endogenous in all IO models.

Estimating the impacts of shocks to the supply of products and labour by means of the standard IO model, however, is impossible for several reasons. First and foremost, firms will not react to negative supply shocks by proportionally reducing all their purchases. Instead they will look for substitutes. Three broad types of replacements are possible. (1) Firms may look for different firms in the same region that produce the same product. This will lead the changes of the *industry market shares* in the supply of the product at hand. This fixed ratio assumption is hidden in the construction of most symmetric IO tables (Miller and Blair 2009). (2) Firms may look for suppliers from different regions. This leads to changes in the *self-sufficiency ratios* and the *imports ratios* for the product at hand. This assumption is mostly made implicitly, but is well recognized in the IO literature (Oosterhaven and Polenske 2009, Miller and Blair, 2009). (3) Firms may look for different products that perform the same function, e.g., plastic subparts instead of metal subparts. This implies a change in the real *technical coefficients*, which is the least likely reaction, at least in the short run, as it implies changing the production process.

Only if an input is truly irreplaceable, the lack of its supply may force purchasing firms to shut down part or all of their production. In that case *processing coefficients* (i.e., reciprocal real technical coefficients) need to be used (Oosterhaven 1987), which results in partial disaster multipliers that will be many times larger than even the large, above mentioned disaster multipliers. In all other cases, substitution of the lacking inputs will lead to positive impacts elsewhere in the economy, including other industries in the same, and in other regions and countries.

Up till now, these positive substitution effects can only be estimated by spatial computable general equilibrium (CGE) models (cf. Tsuchiya et al. 2007). In fact, different versions of such a model are needed to model the short run as opposed to the longer run impacts, because short run substitution 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 modeled endogenously. Consequently, CGE models are difficult and rather costly to estimate, even if the essential data, such as interregional social accounting matrices and all kind of elasticities, are available (see Albala-Bertrand 2013, for further critique).

The hypothetical extraction (HE) method, proposed by Dietzenbacher and Miller (2015) as an alternative to the IO model, circumvents assuming of fixed trade coefficients, because a well-defined HE involves the assumption that the sales of the extracted industry are compensated by an equally large increase of imports (see Dietzenbacher & Lahr 2013, for extensions of the original HE method). However, contrary to what was originally suggested (Paelinck et al. 1965; Strassert 1968), the complete or partial extraction of a row from the IO matrix does not simulate the forward, supply impacts of that HE on its customers. Instead it measures the backward, demand effects of a drop (or complete disappearance) of demand for the intermediate inputs of the extracted industry.

The supply-driven IO model (see Bon 1988, for the multiregional version) does not constitute a plausible model for studying the forward impacts of disasters either (see Oosterhaven, 1996; 2012, and Dietzenbacher, 1997, who additionally advocates a reinterpretation as a price model). Presently, a more or less plausible measurement of the economy-wide impacts of an exogenous supply shock, requires many additional assumptions and/or information as regards the adaptation behaviour of upstream and downstream industries, as in Oosterhaven (1988), Hallegate (2008), and Rose and Wei (2013).

As a simpler alternative to using fixed ratios, Batten (1982, chapter 5) shows how the principle of minimum information gain (cf. Theil 1967) may be used to flexibly estimate intra- and interregional trade flows in various multi-regional input-output (MRIO) settings. This principle is also applicable to a situation wherein a shock to a MRIO system results in lower production capacities with an unknown new pattern of intra- and interregional trade. Oosterhaven and Bouwmeester (2016) combine this idea with processing coefficients and endogenous production levels in the indirectly impacted industries and regions. In this paper we follow their approach, but instead of using an interregional IO table, we use the nowadays more common multi-regional supply-use table (MRSUT) framework to describe the various equilibriums. In this way we are also able avoid the assumption of fixed industry market shares, which is still present in their MRIO approach.

In Section 2, we present our new, MRSUT non-linear programming (NLP) model. Section 3 presents the specification of the main flooding scenario and two scenarios describing the flooding impacts under alternative economic environments. First, we consider the case of extensive governmental aid and, second, we consider the case where all pre-disaster production capacities are fully utilized, as at the top of the business cycle. Our results in Section 4, show considerably lower disaster multipliers in the main and in both alternative scenarios compared to those found with standard demand-driven IO models. In Section 5, we investigate the overestimation of the indirect impacts that results when our assumptions of flexible trade origin shares and flexible industry market shares are replaced with fixed shares, as in the standard MRIO model. Section 6 concludes.

2. Modelling methodology

Our simulation of the short run reaction of economic actors (firms, households and various governments) to a disaster is based on the assumption that all actors attempt to re-establish the size and pattern of their economic transactions of the pre-disaster situation as much as possible. We measure the distance between the situation before and after the disaster by means of the information gain measure of Kullback (1959) and Theil (1967). To mimic the adaptation strategies of economic actors, we minimize the information gain of the short run post-disaster equilibrium compared to pre-disaster equilibrium of the economy at hand, i.e., the base scenario, as summarized by the 2007 MRSUT of Germany (Többen 2014).

The set-up of this table is shown in Figure 1, with bold capital cases indicating matrices, bold lower cases vectors and italics scalars, and where:

$v_{ij}^{r} \in \mathbf{V^r}$ = supply of product j by industry i in region r,

$u_{ji}^{rs} \in \mathbf{U^{rs}}$ = use of product j from region r by industry i in region s,

$y_{jf}^{rs} \in \mathbf{Y^{rs}}$ = use of product j from region r by final demand category f in s,

$e_j^r \in \mathbf{e^r}$ = foreign exports of product j by region r,

$w_{li}^r \in \mathbf{W^r}$ = value added type l by industry i in region r,

$g_j^r \in \mathbf{g^r}$ = total supply = total demand of product j by region r,

$x_i^r \in \mathbf{x^r}$ = total output = total input by industry i in region r,

$u_{ji}^{RoW,s} \in \mathbf{U^{row,s}}$ = foreign imports of product j by industry i in region s,

$y_{jf}^{RoW,s} \in \mathbf{Y^{RoW,s}}$ = foreign imports of product j by final demand category f in region s,

* = summation over the index concerned

<Figure 1 about here>

The information measure of Kullback and Theil, however, needs to be adapted to incorporate the criticism that arose in the discussion that unrolled after the introduction of the GRAS algorithm for updating and regionalizing national IO matrices with both positive and negative entries (Junius and Oosterhaven 2003). Huang et al. (2008) summarize this discussion and propose an improved GRAS objective function (IGRAS). We use the IGRAS measure and not their comparably well performing improved normalized squared differences, as the latter concentrates on minimizing large percentage errors in small cells, while it treats positive and negative deviation equally, as opposed to IGRAS that weighs negative deviations (i.e., losses) more heavily than positive ones (i.e., gains). However, our actually used version of IGRAS is a little simpler than that of Huang et al., as we do not have negative entries (see further Oosterhaven and Bouwmeester, 2016).

In summary, we thus *minimize* the *information gain* of the post-disaster MRSUT compared to the pre-disaster MRSUT:

$$Minimize\ \sum_{ij}^{r} v_{ij}^{r,ex}\left(\ln\frac{v_{ij}^{r}}{v_{ij}^{r,ex}}-1\right)+\sum_{ij}^{rs} u_{ij}^{rs,ex}\left(\ln\frac{u_{ij}^{rs}}{u_{ij}^{rs,ex}}-1\right)+\sum_{j}^{rs} y_{j*}^{rs,ex}\left(\ln\frac{y_{jf}^{rs}}{y_{j*}^{r,ex}}-1\right)+$$

$$\sum_{j}^{r} e_{j}^{r,ex}\left(\ln\frac{e_{j}^{r}}{e_{j}^{r,ex}}-1\right)+\sum_{i}^{r} w_{*i}^{r,ex}\left(\ln\frac{w_{li}^{r}}{w_{li}^{r,ex}}-1\right) \tag{1}$$

In (1), the summation over r in the terms with u_{ij}^{rs} and y_{jf}^{rs} (i.e., in the regionalized Use table) includes the Rest of the World (RoW). The * indicate that we aggregate, respectively, the ten categories of final demand and the five categories of value added of the MRSUT. The *ex* indicates exogenous data (i.e., the actual values from the MRSUT for Germany for 2007). For our application to the German floods we use an aggregated version of the original table, with 12 industries and 19 products, in order to keep the computational requirements at a reasonable level.[1] A description of the industry and product categories is shown in Table 1.

<Table 1 about here>

The first restriction to minimizing (1) is that all *transactions* are *semi-positive*. This implies that changes in stocks are excluded from the model. This exclusion is justified by the fact that changes in stocks, as a rule, do not represent economic transactions for which we assume that economic actors try to maintain them as much as possible. The pre-disaster *levels* of stocks, however, do represent important ultra-short run adaptation possibilities (see Hallegate 2008, Mackenzie et al. 2012). Hence, these are ignored by our method; partly because they only delay the adjustments that are modelled by our method, and partly because a MRSUT only gives information about the historic *changes* in these levels and not about the levels themselves.

Furthermore, in all scenarios we minimize (1) subject to the following additional constraints.

First, and foremost, we assume that prices changes in such a fashion that the economy remains in short run equilibrium, i.e., we assume that *demand equals supply*, per product, per region:

$$\sum_i^s u_{ji}^{rs} + \sum^s y_{j*}^{rs} + e_j^r = \sum_i v_{ij}^r \,,\ \forall j, r \tag{2}$$

A great advantage of our approach, above that of, for example, a CGE model, is that we do not need to specify these price changes nor do we need to specify any supply or demand elasticities. Instead we concentrate on the volume changes, i.e., all variables are measured in base scenario prices equal to unity.

Second, and equally important, we assume that *total output equals total input* for each regional industry:

$$\sum_j v_{ij}^s = \sum_j^r u_{ji}^{rs} + w_{*i}^s \,,\ \forall i, s \tag{3}$$

Third, we assume cost minimization under a *Walras-Leontief production function*, per input, per industry, per region, which results in (Oosterhaven 1996):

$$\sum^r u_{ji}^{rs} = a_{ji}^{*s} x_i^s,\ \forall j, i, s, \text{ and } w_{*i}^s = c_i^s x_i^s,\ \ \forall i, s \tag{4}$$

In (4), additionally, a_{ji}^{*s} denote fixed technical coefficients, i.e. intermediate inputs regardless of spatial origin per unit of output, and c_i^s denotes fixed value added per unit of output, with the a_{ji}^{*s} and c_i^s being calculated from the base-year MRSUT as $a_{ji}^{*s} = \sum^r u_{ji}^{rs,ex} / x_i^{s,ex}$ and $c_i^s = w_{*i}^{s,ex} / x_i^{s,ex}$. Note that $\sum_j a_{ji}^{*s} + c_i^s = 1 \,,\ \forall i, s$, by definition and, therefore, that *r* in (4) as well as the summation * includes foreign imports.

Fourth, we use the same assumption to model a *fixed product mix of final demand*:

$$\sum^{r} y_{j*}^{rs} = p_j^s y^s, \ \forall s \qquad (5)$$

In (5), additionally, y^s denotes total regional final demand (i.e., $\mathbf{i'y^s}$), and the p_j^s denote package coefficients (i.e., final demand regardless of spatial origin per unit of total final demand), with the p being calculated from the base-year MRSUT as $p_j^s = \sum^r y_j^{rs,ex}/y^{s,ex}$, with $\sum_j p_j^s = 1$. Note that (5) may be derived from a cost minimizing assumption under a Walras-Leontief utility function, and note again that *r* includes foreign imports.

3. The flooding scenarios

In May and June 2013 heavy rainfalls over Central Europe led to massive floods of the rivers of Elbe, Danube and their tributaries. For the particularly affected states of Sachsen and Sachsen-Anhalt it was already the third "flooding of the century" since 1997. In the future, floods are expected to occur even more frequently due to climate change (IPCC 2013, PIK 2011). According to annual reports of the re-insurance company Munich Re (2014), the floods were the world's most costly natural disaster in 2013, with economic damages estimated at about 10 b€ to German public infrastructure, rolling stock, factories and residential buildings.

This figure, however, only accounts for insurance claims for direct damages to capital *stocks*. In addition, the floods also caused substantial damages by restricting economic activity (i.e., *flows* representing economic transactions). In the case of the 2013 floods such damages include, for example, business losses of manufacturers that had to shut down production because production facilities were damaged or because workers were unable to get to work as well as losses of business owners in the affected cities, who had to close their hotels, restaurants or stores (Wenkel 2013). These *direct* business losses constitute the cause for further indirect losses in upstream and downstream industries. The estimation of the latter losses constitutes the main purpose of our model. As there is no exact information on the direct losses, we use monthly data about the number of employees *working 'undertime'* to estimate the production losses directly caused by the floods.

3.1 The Main flooding scenario

In the Main flooding scenario, we model these *direct* production losses as constraints on the production capacities of industries in the directly affected regions. This set of regions q consists of the four out of the sixteen German States whose economies were directly hit by the floods. These are Bayern in southeast, whose economy was hit by a flood of the river of Danube, and the eastern German regions of Sachsen, Sachsen-Anhalt and Thüringen, whose economies were hit by the flooding of the river of Elbe (see Figure 3 for the location of these regions). Direct damages to production capacities are modelled by

$$x_i^q \leq \left(1 - \gamma_i^q\right) x_i^{q,ex}, \forall\, i, q \qquad (6)$$

where γ_i^q represent the production capacity loss rate of industry *i* in region *q*.

The losses of production capacities are taken from Schulte in den Bäumen et al. (2015), where they are estimated by means of monthly data about the number of workers *working undertime* by region and industry.[2] Figure 2 shows the monthly time series of the number of undertime employees in Germany from January 2008 to December 2014. Due to the seasonal climate, this number usually increases from summer to winter and decreases from winter to summer, since the cold weather hampers many sectors, such as agriculture, construction and gastronomy. The data point marked by a grey arrow refers to the maximum reached in 2009 in the course of the financial crisis. In that year the German GDP dropped by about 5.2%. The data points marked by a white arrow in 2013 and 2014 refer to increases of the number of undertime employees that are caused by unusually wet springs. In the bottom panel, the strong increase from May to June 2013 (marked by a black arrow) can be attributed to the flood of the Danube and the Elbe. In the flooded regions of Bayern, Sachsen, Sachsen-Anhalt and Thüringen undertime employees make out about 0.263%, while in those regions unaffected by the flood only 0.006% of employees are working undertime.

In the short run that we are studying, the labour-intensity of production may be assumed to be fixed. Consequently, the shares of employees working undertime delivers our estimates of the production capacity loss rates γ_i^q.

<Figure 2 about here>

For the interpretation of the spatial distribution of the flooding impacts, the first panel of Figure 3 shows the geographical location of the 16 German states. The second panel shows the population and GDP shares of the German regions. From these numbers it can be concluded that there is still a significant gap in GDP per capita between the former western and eastern Germanys. The highest GDP per capita can be observed for the city states of Hamburg and Bremen. Berlin's GDP per capita is below the national average, but significantly higher than the GDP per capita of the other eastern states. These high city state scores, however, are misleading as an indicator for regional welfare, as they are partly explained by the large amounts of in-commuters that do not count in the denominator. Apart from the city states, the southern states of Bayern, Hessen and Baden-Württemberg have the highest GDP per capita. In both former parts of re-unified German, GDP per capita increases from north to south. Among the former western states, the most northern state of Schleswig-Holstein has the lowest GPD per capita, while among the former eastern states Sachsen in the south has the highest and Mecklenburg-Vorpommern in the north has the lowest GDP per capita.

Finally, the rightmost column shows the percentage inoperability, i.e., the direct loss of production capacity in the four directly affected regional economies. The inoperability of Bavaria’s economy turns out to be much lower compared to the three eastern states that are hit by the Elbe floods. However, the size of Bavaria´s economy is more than twice as large as the economies of Sachsen, Sachsen-Anhalt and Thüringen taken together, which makes the absolute size of its inoperability, in fact, larger than that of the three Elbe regions. In a recent contribution, Thieken et al. (2016) present outcomes from a survey among 550 firms, of which 88% reported business losses. Their outcomes show sectoral differences regarding the nature of the business interruptions. Manufacturers mostly suffered from own delivery problems and delivery problems of suppliers, whereas service sectors were mostly affected by sales reductions.

<Figure 3 about here>

3.2 The Alternative economic environment scenarios

In the first alternative scenario, we assume that the German government reacts to the drop in income in the flooded regions by strong policy measures such that the level of final demand is maintained in all regions. This *Governmental Aid scenario* implies adding the following constraint to the Main flooding scenario (1)-(6):

$$y^s \geq y^{s,ex}, \forall\ s. \tag{7}$$

In the second alternative scenario we assume that all industries in all of Germany have zero excess production capacity, as would be about the case at the top of the business cycle. The Main flooding scenario, which assumed unlimited spare capacity in all of Germany, of course, comes closer to the actual situation in June 2013. In fact, Figure 2 shows that the Germany's economy was hit by the floods at the seasonal bottom of the business cycle, when GPD grew by only 0.1% in the first quarter, due to a long winter and an unusually wet spring (Wenkel 2013).

Mathematically, this second alternative, *Business Cycle scenario* implies adding the following constraint to the Main flooding scenario (1)-(6):

$$x_i^s \leq x_i^{s,ex}, \forall\, i, s. \tag{8}$$

4. Modelling outcomes

Before discussing the three flooding scenarios, we first summarize the properties of the short run pre-disaster equilibrium, i.e., the *Base scenario*. It consists of the transactions shown in the MRSUT for the 16 German States for 2007 (Többen 2014). However, from this MRSUT, the negatives have been removed, which means that the accounting identities (2) and (3) are no longer observed. Hence, with the base model (1)-(3) the MRSUT is re-balanced, and the technical coefficients of (4) and (5) are re-calibrated. The removal of negative flows and the re-balancing of the MRSUT only leads to small differences between the original table and the *Base scenario* table. The mean absolute percentage deviation of MRSUT elements amounts to 1.31%, while the weighted mean absolute percentage deviation is only 0.67%, which indicates that the larger percentage deviations tend to concentrate on the smaller elements.

4.1 Outcomes of the Main flooding scenario

The impact of the floods in the Main flooding scenario is shown in Table 2 in terms of the difference between the aggregated pre-disaster and post-disaster multiregional Use tables.

Nationwide, gross output drops by b€ 3.27. With a loss of output in the flooded states directly caused by the disaster of about b€ 2.95, this outcome implies a national German disaster multiplier of 1.11. Formally, we define the national disaster multiplier as:

$$M^N = \sum_i^s \left(x_i^s - x_i^{s,ex}\right) / \sum_i^q \gamma_i^q x_i^q, \tag{9}$$

where the numerator represents the *total* national change in gross output and the denominator represents the change in output that can be directly attributed to the floods. Note that the national multiplier comprises both, negative and positive impacts on regional industries, such that it has to be interpreted as a *net* multiplier. In the Main flooding scenario, the total net impact comprises aggregate regional losses of about b€ 3.36 and aggregate regional gains of about b€ 0.09, which only occur in non-flooded regions, as their industries are not affected by the direct capacity losses.

<Table 2 about here>

Regarding the four flooded states, regional multipliers vary from 1.139 for Bayern (r9) via 1.041 for Sachsen (r14), 1.046 for Thüringen (r16) to virtually 1.0 for Sachsen-Anhalt (r15). These regional disaster multipliers are defined as:

$$M^q = \sum_i^q \left(x_i^q - x_i^{q,ex}\right) / \sum_i^q \gamma_i^q x_i^q, \tag{10}$$

where the numerator measures the *total* change in regional gross output of flooded states and the denominator measures the *direct* loss of gross output due to the floods in that same state.

The main reason for the difference in the regional multipliers is the relative size of Bayern's economy, which is more than twice as large as the economies of Sachsen, Sachsen-Anhalt and Thüringen taken together (see Figure 3). Larger regions tend to be less open and, hence, tend to be relatively more dependent on intraregional transactions, which are shown on both the diagonals in the top-panel (intraregional industry-to-industry transactions) and in the bottom-panel (intraregional industry-to-final demand transactions) of Table 2. The elements of both off-diagonals, in contrast, refer to interregional transactions.

In all four cases, the regional disaster multipliers are small, definitely compared to the impact multipliers derived from the standard, demand-driven Leontief model (e.g., the weighted average IO multipliers of the flooded regions run from 1.38 for Sachen-Anhalt to 1.45 for Bayern). They are even smaller when compared to the disaster impact multipliers deduced from the papers cited in Section 1. The main reason for this difference is that our model takes spatial substitution effects into account, whereas IO multipliers do not.

Compared to the negative direct impacts and the negative first order indirect forward and backward impacts, these positive substitution effects are much smaller and, thus, only mitigate the negative direct and first order indirect impacts in the rows and columns of the flooded regions. In the off-diagonal cells of the non-flooded regions, however, no direct and first order indirect negative impacts are present. Consequently, practically all of these cells in Table 2 appear to be positive, indicating that the positive substitution effects dominate the higher order negative effects for the non-flooded regions.

With respect to the regions that only experience indirect impacts, large impacts can, in particular, be found in Nordrhein-Westfalen (r5), Hessen (r7) and Baden-Württemberg (r8), which are ranked first to fourth in terms of their share in national GDP. Moreover, Baden-Württemberg and, especially, Hessen share long common borders with flooded states and have strong economic interrelations with, especially, Bayern. In addition, the city state of Hamburg (r2) shows remarkably large reductions of its gross output for the relatively small size of its economy and its rather long distance from the regions directly affected. This outcome can be attributed to the important role of Hamburg as a transportation hub for international trade. Germany's largest sea harbor is located here, while the Elbe directly connects Hamburg with the three flooded eastern states. The fact that deliveries from Sachsen and Sachsen-Anhalt that satisfy intermediate and final demand in Hamburg are affected in particular, provides further support for this interpretation.

<Table 3 about here>

Regarding the changes in final demand, shown in the lower part of Table 2, drops can be observed in all regions. The drops in the non-flooded states can be explained by the shortage of supply, especially of manufactured products from the flooded states. The purchases of these products from local suppliers, from other non-flooded states and from the rest of the world increase, but these increases are insufficient to fully compensate for disaster induced losses of supply. The drops in intraregional deliveries to final demand on the diagonal of the lower part of Table 2 stem from decreased final demand for personal services, which are predominantly non-tradable. This means that the suppliers of these services are unable to compensate for the drops of local demand by searching for new customers in other regions.

Regarding the impacts on value added, Table 3 adds a breakdown by industry to the breakdown by region shown in Table 2. In the Main flooding scenario, the total impact on value added amounts to a loss of about b€ 1.43, whereby about 84% or b€ 1.2 of the total impact on value added can be attributed to the direct loss of production capacities. The remainder of about b€ 0.227 constitutes the net indirect impact of the disaster. This net impact to value added consists of a positive component of about m€ 38 (the sum of positive changes in value added by regional industry in Table 3) and of a negative component of about m€ 265. About 58% of the indirect net impacts concentrate on those regions that are already directly affected by the disaster, whereby Bayern (r9) is particularly affected. Out of those regions that are only indirectly affected, the largest absolute impacts are felt in Nordrhein-Westfalen (r5), Hessen (r7), Baden-Württemberg (r9) and the city-state of Hamburg (r2).

Regarding the impacts by industry it can be seen that the construction sector (i8) in the non-flooded regions experiences an increase in its output and, thus, in its value added of about m€ 35. This outcome can be explained by an important peculiarity of this sector, namely that it sells its output almost exclusively to the capital formation part of regional final demand. As such, the construction sector suffers from the indirect drop of final demand just like personal service. However, unlike personal services, construction services are more mobile, since construction firms may send their workers to construction yards in other regions. Consequently, construction firms from non-flooded states step-in to compensate for the supply shortage in flooded states, which more than offsets the drop of construction demand from final consumers in their own regions.

In terms of negative indirect impacts, a concentration on just three sectors can be observed, namely trade services and gastronomy (i9), financial and business related services (i11), and personal services (i12), which account for about 83% of all negative impacts. This outcome can be explained by the drop of final demand in the flooded regions, which predominantly hits industries with a high dependency on local demand.

4.2 Outcomes of the Alternative economic environment scenarios

Next, we discuss how the outcomes of the Main flooding scenario change under different economic environments.

In the *Governmental Aid scenario* it is assumed that governments prevent regional final demand to drop below its pre-disaster level. It can be observed from Table 4 that this scenario has a large positive effect on the indirect impacts on value added. In fact, the total increase in value added by m€ 320, compared to the Main flooding scenario, means that the total damage of the flood is reduced by about m€ 93. Consequently, the national net disaster multiplier is less than one (0.939), while regional net multipliers are close to one (i.e. the largest multiplier is that of Bayern (r9) with about 1.020).

The regional distribution of impacts shows that the positive impact of governmental aid on regional value added is substantial enough to offset the losses observed in the Main scenario in the states directly affected by floods. This result gives additional support for our interpretation that the majority of indirect losses are the result of drops in final demand levels as a reaction on the supply shortage, rather than being caused by the supply shock itself. This particularly holds true for industries providing personal services primarily to local markets.

In non-flooded states by contrast, the indirect gains of Governmental Aid on value added offsets the indirect losses observed in the main scenario, as the national multiplier already suggests. However, there is a remarkable difference between the impact of Governmental Aid on manufacturers (i1 to i6), as opposed to the impact on public utility (i7), construction and services industries (i7 to i12), indicating that in particular the industries that depend on local markets benefit from such a policy. Manufacturing industries are already much smaller than the service industries (see Table 1), but even discounting this size effect, they also benefit less from preventing regional final demands to drop; some of them even suffer additional losses. This outcome suggests that supporting final demand may result in increased competition for already limited supply.

<Table 4 about here>

In the *Business Cycle scenario* it is assumed that the regional economies are hit at the top of the business cycle, i.e., that all regional industries are operating at full capacity. Table 5 examines the impacts of this scenario. The limited ability to purchase substitutes from German firms has a substantial impact on the national net disaster multiplier, which increases from 1.139 to 1.183. About 93% of these additional indirect losses occur in non-flooded states that are now unable to compensate for the supply shortages in the flooded states. The regional multipliers of flooded states increase only slightly; in Bayern (r9) from 1.139 to 1.149, in Sachsen (r14) from 1.046 to 1.048, and in Thüringen (r16) from 1.041 to 1.043. In Sachsen-Anhalt (r15) the net multiplier remains almost unchanged. Our main outcome that economies at the top of the business cycle are more vulnerable to supply shocks is in line with results derived from an endogenous business cycle model reported by Hallegate and Ghil (2008).

The distribution of indirect losses across industries is also different, compared to the Main flooding scenario. Intuitively, one would expect that manufacturers in non-flooded states are among those industries who suffer most from limited production capacities. Due to their typically higher share of intermediate inputs in total cost of production compared to service industries, manufacturers are more dependent on finding substitutes for supply lost from the flooded states. Still, even discounting the much smaller size of the manufacturing industries compared to the service industries, about 98% of indirect losses of value added are felt by service industries delivering primarily to local final demand. This outcome suggests that limited production capacities in non-flooded states at the top of the business cycle amplify the indirect demands shock in the form of a drop of final demand, which were switched off in the *Governmental Aid* scenario, but not in the *Business Cycle* scenario. From this general pattern some exceptions can be found among the industries from the primary sector, manufacturing and utility (i1-i7), which are mainly driven by exports.

<Table 5 about here>

5. Testing the impact of assuming fixed ratios

Next, we discuss how the results of the Main flooding scenario would change, if we add the additional assumptions of the demand-driven MRIO model to our NLP model (1)-(6), namely fixed trade origin shares and fixed industry market shares in regional product demand. Investigating the impacts of adding these two assumptions alone and in combination enables us, firstly, to examine the scale of damages that are avoided because of the ability of industries and final consumers to search for different suppliers when faced with a supply shortage. Secondly, it enables us to assess the potential overestimation of the indirect disaster impacts when MRIO models are used that do not allow for these substitution possibilities.

5.1 Fixed market shares and fixed trade coefficients

The assumption of *fixed industry market shares* is commonly used in IO models based on industry-by-industry transaction matrices, both in the case when such models are based on supply-use tables (SUTs) and when they are based on symmetric industry-by-industry IO tables. In the first case the assumption needs to be made explicitly in order to derive an operational IO model (Oosterhaven 1984). In the second case, the assumption is implicitly embodied in the symmetric IO table itself, which nowadays are typically derived from supply-use accounts (see Miller and Blair 2009). Formally, the assumption of fixed market shares is written as

$$v_{ij}^r = d_{ij}^r g_j^r, \forall\, i, j, r. \tag{11}$$

where d_{ij}^{r} = market share of industry *i* in the demand for product *j* from region *r*, calculated from the MRSUT, with $\sum_i d_{ij}^{r} = 1$.

While this assumption is, to some extent, plausible when used in the context of a negative demand shock, it is highly implausible when the economy is faced with a negative supply shock. This can be easily shown with an example. Assume the extreme case where a certain product is produced by two industries only. The first industry is assumed to provide 90% of the total supply, whereas the market share of the second industry is only 10%. If this second industry is forced to shut down its production because of a disaster while the first industry is unaffected, fixed industry market shares would imply that the first industry will also not be able to sell that product. Therefore, the assumption of fixed market shares can be expected to inflate the outcomes of our model artificially.

The assumption of *fixed trade origin shares* is commonly used in all demand-driven MRIO and MRSUT models (cf. Oosterhaven 1984). As the data are available, we use the cell-specific, so-called interregional version of this assumption (Isard 1951), instead of the less data demanding row-specific, so-called multi-regional version (Chenery 1953; Moses 1955). Formally, the cell-specific version is written as

$$u_{ji}^{rs} = t_{ji}^{rs} u_{*i}^{s}, \forall\, r, s, j, i, \tag{12}$$

for intermediate demand, and

$$y_{jf}^{rs} = t_{jf}^{rs} y_{*f}^{s}, \forall\, r, s, j, f, \tag{13}$$

for final demand, where t_{ji}^{rs} and t_{jf}^{rs} indicate the trade origin shares, i.e., the output of product *j* from region *r* per unit of total use of product *j* by industry *i* in region *s* or by final demand category f in region *s*. These shares are calculated from the MRSUT, with $\sum^{r} t_{ji}^{rs} = 1$

and $\sum^r t_{jf}^{rs} = 1$. The row-specific version of (12)-(13) assumes that the trade origin shares for all purchasing industries j and all purchasing final demand categories f in region s are equal.

In terms of intermediate demand, the assumption of fixed trade shares extends the fixed technology assumption to the geographical origin of intermediate inputs (cf. Oosterhaven & Polenske 2009). In the context of a negative demand shock, it is more or less plausible to assume that firms proportionally purchase less inputs from all their established suppliers. In the case of a negative supply shock, however, firms will immediately search for different sources for their inputs. In an extreme case, assuming fixed trade shares implies that firms have to shut down their own production completely if only one of their suppliers from a specific region is not able to deliver the required inputs. The same holds true for final consumption. Hence, this standard MRIO assumption also leads to overstating the indirect impacts of disasters.

5.2 Discussion of the effect of assuming fixed ratios

In order to examine the effect of these standard IO assumptions on the scale and spread of indirect impacts, national and regional impact multipliers of the Main flooding scenario under the three different sets of assumptions are shown in Table 7. These sets include, first, the assumption of fixed market shares, second, the assumption of fixed trade shares and, third, both assumptions taken together.

<Table 7 about here>

It can be observed that all three sets of alternative assumptions have a significant impact on the scale of the projected indirect impacts. Fixed industry market shares amplify indirect impacts by more than 75% compared to the Main flooding scenario. In particular the strong increase in Bayern (r9) is responsible for this result. In Bayern, the machinery and transport equipment sector (i6) experiences a direct loss of production capacity of about 0.27%. This industry produces 12 different types of secondary products in addition to its primary products. As these secondary products constitute the primary product of 9 other industries, the strong shock to i6's production capacity is transferred onto these 9 other industries by forcing them to decrease their production in accordance to their pre-disaster market shares.

Under fixed trade origin shares the national disaster multiplier is amplified even more, i.e., with about 140% compared to the Main flooding scenario. Compared to the assumption of fixed market shares, the regional multiplier of Bayern is significantly smaller, while those of the eastern states increase. The much smaller increase in the regional multipliers compared to the national one indicates that substantial fractions of the indirect losses are felt in non-flooded states. The main reason for the inflated national multiplier are the much smaller positive indirect impacts in non-flooded states, as spatial substitution has been ruled out.

Finally, combining both assumptions mimics the impacts as estimated by the demand-driven MRIO model. It can be seen that the combination of both assumptions drastically amplifies the estimated scale of the indirect damages. The national disaster multiplier becomes 1.971, which means that nationwide indirect damages are about six times larger compared to the Main flooding scenario. This means that they are now of an order magnitude that is comparable order to the lower end of the bandwidth of multipliers reported in the literature on the IO model cited in Section 1.

Our outcomes of adding both assumptions also confirm the outcomes of Koks et al. (2015). They compare the regional and national disaster impacts of two flooding scenarios for the Italian Po river delta, as estimated with, respectively, the adaptive regional input-output (ARIO) model developed by Hallegate (2008), a regionalized version of the CGE model developed Standardi et al. (2014), as applied in Carerra et al. (2015), and the multi-regional impact assessment (MRIA) model of Koks and Thissen (2016).The latter model resembles our own approach most. Both with a convex and with a linear recovery path, which phenomenon is absent in our approach, the fixed ratio ARIO approach predicts national economic losses that are 1.5 to 3 times larger than those of the more flexible ARIO and CGE models.[3] With a concave recovery path, the ARIO model outcomes are 4.5 to 7 times larger than those of the MRIA model and almost 6 times larger than those of the CGE approach. Without the mitigating positive impact of the recovery path assumptions, the difference would be even larger.

6. Conclusion

This paper assesses the indirect economic losses caused by the heavy flooding in the south and south-east of Germany in 2013 by means of the novel non-linear programming (NLP) model originally proposed by Oosterhaven and Bouwmeester (2016). It constitutes the first application of that method to a real disaster using a multiregional supply-use table, instead of a multiregional input-output table.

First and foremost, we remarkably find regional and national disaster multipliers all to be smaller than 1.20. Second, we examine the sensitivity of the NLP model outcomes to varying economic environments, which shows that government support of final demand substantially reduces the already small indirect losses, while being at the top of the business cycle considerably increases them.

Third, we investigate the implications of adding the fixed ratio assumptions commonly used in IO models. We theoretically conclude that the applying fixed origin trade shares and fixed industry market shares, in the presence of negative supply shocks, has implausible economic implications, while our empirical outcomes show that they artificially enlarge the indirect disaster loss estimates by about 70% and 140%, respectively. When both fixed ratios are added in combination, as in all standard IO models, indirect disaster loss estimates are amplified about six times.

As regards the choice of modelling technique, we conclude that the NLP model fills the huge gap between standard IO models of questionable plausibility in case of supply shocks and fully articulated spatial computable general equilibrium (SCGE) models that have extreme data requirements. The NLP model has the advantage of allowing for flexibility in trade origin shares and industry market shares, without needing to model prices and markets explicitly as in SCGE models.

Finally, our much lower disaster multipliers than hitherto reported have an important policy implication. They imply that the disaster literature emphasis on stimulating the resilience of the economic system as a whole is not justified. Instead, much more attention to preventing and mitigating the direct cost of natural and man-made disasters is justified.

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Table 1. Industry and product categories, with national value added shares per industry

Industries			Products	
Code	Description	% value added	Code	Description
i1	Agriculture, Forestry, Fishery	1,2%	j1	Agriculture, Forestry, Fishery
i2	Mining and Quarrying	0,4%	j2	Mining and Quarrying
i3	Food, Textiles, Wood products, Paper, Printed Matter	4,1%	j3	Food, Textiles
i4	Refined Petroleum, Chemicals, Plastics	4,2%	j4	Wood products, Paper, Printed Matter
i5	Glass, Mineral Products, Basic and Fabricated Metals	4,1%	j5	Refined Petroleum
i6	Machinery, Transport Equipment, other Manufacturing	12,0%	j6	Chemical and Plastic Products
i7	Electricity, Gas and Water Supply	2,5%	j7	Glass and Mineral Products
i8	Construction	4,1%	j8	Basic and Fabricated Metals
i9	Trade Services, Hotels and Restaurants	11,4%	j9	Machinery
i10	Transportation	5,9%	j10	Electrical Apparatus and Equipment
i11	Financal Intermediation, Renting, Business-related Services	28,3%	j11	Transport Equipment
i12	Public Administration, Education, Healthcare, Personal Services	21,9%	j12	Furniture and other manufactured products
			j13	Electricity, Gas and Water
			j14	Construction
			j15	Trade, Hotels and Restaurants
			j16	Transport Services
			j17	Telecommunication
			j18	Financal Intermediation, Renting, Business-related Services
			j19	Public Administration, Education, Healthcare, Personal Services

Table 2. Difference between aggregated pre- and post-disaster transactions (m€) in the Main flooding scenario

	Intermediate Use																
	r1	r2	r3	r4	r5	r6	r7	r8	**r9**	r10	r11	r12	r13	**r14**	**r15**	**r16**	**...**
r1	2.1	-0.2	0.2	0.0	0.6	0.1	0.1	0.3	-1.6	0.0	0.1	0.1	0.1	-1.3	-1.3	-1.5	...
r2	0.7	2.0	1.4	0.1	0.7	0.2	0.4	0.7	-2.8	0.1	0.3	0.3	0.3	-4.0	-4.6	-2.9	...
r3	0.2	1.9	4.9	0.2	1.2	0.2	0.4	2.7	-6.1	0.1	0.2	0.2	0.1	-6.0	-7.1	-3.6	...
r4	0.0	0.0	0.2	0.3	0.4	0.1	0.1	0.2	-1.1	0.0	0.0	0.0	0.0	-2.1	-0.7	-0.7	...
r5	0.4	0.7	1.6	0.3	10.5	0.8	1.0	2.9	-24.7	0.2	0.6	0.4	0.3	-16.7	-14.8	-8.6	...
r6	0.1	0.2	0.3	0.1	0.7	0.5	0.3	1.7	-3.5	0.0	0.2	0.1	0.2	-2.6	-2.2	-1.5	...
r7	0.2	0.2	1.3	0.2	2.5	0.7	4.2	1.1	-10.4	0.1	0.1	0.1	0.1	-8.0	-6.8	-6.4	...
r8	0.3	1.2	1.2	0.0	1.9	0.6	0.8	9.1	-14.0	0.3	0.4	0.4	0.2	-9.5	-6.9	-4.3	...
r9	-1.5	-1.9	-6.4	-0.9	-16.6	-2.6	-5.7	-12.6	-439.7	-1.1	-1.2	-1.1	-0.9	-19.0	-11.9	-9.3	...
r10	0.1	0.2	0.1	0.0	0.7	0.1	0.1	0.2	-1.5	0.4	0.0	0.1	0.0	-1.1	-0.8	-0.6	...
r11	0.1	0.0	0.2	0.0	0.6	0.1	0.1	0.3	-2.2	0.0	1.5	0.1	0.1	-4.1	-4.5	-1.2	...
r12	0.1	0.5	0.2	0.0	0.4	0.1	0.2	0.8	-1.4	0.0	0.4	1.4	0.1	-3.2	-2.5	-0.7	...
r13	0.0	0.0	0.1	0.0	0.4	0.0	0.1	0.1	-0.8	0.0	0.0	0.0	-0.1	-1.1	-0.7	-0.5	...
r14	-1.9	-4.6	-4.6	-0.3	-9.9	-1.4	-4.2	-9.5	-15.3	-1.3	-2.5	-1.3	-0.7	-343.4	-7.8	-3.3	...
r15	-2.1	-5.4	-6.4	-1.3	-14.6	-3.0	-5.1	-10.2	-13.0	-1.3	-2.5	-1.7	-1.3	-9.2	-247.7	-5.1	...
r16	-0.8	-0.8	-2.5	-0.7	-6.5	-1.2	-2.9	-4.6	-8.1	-0.4	-0.7	-0.7	-0.4	-4.4	-2.8	-144.3	...
Imports	1.8	1.9	7.1	1.0	11.7	3.1	5.0	12.6	-121.8	1.0	1.4	1.3	0.9	-68.2	-77.0	-34.4	...
VA	-4.5	-13.0	-7.0	-2.0	-22.4	-3.4	-14.3	-11.7	-483.0	-2.8	-7.7	-3.6	-2.3	-405.4	-288.9	-160.3	
Total Output	-4.9	-17.0	-8.2	-2.9	-37.8	-5.1	-19.5	-16.0	-1150.8	-4.5	-9.4	-3.8	-3.3	-909.3	-689.0	-389.3	

	Final Use																Exports	Total Use
	r1	r2	r3	r4	r5	r6	r7	r8	**r9**	r10	r11	r12	r13	**r14**	**r15**	**r16**		
r1	-1.3	-1.4	0.1	0.0	0.2	0.0	0.1	0.2	-0.7	0.1	0.1	0.1	0.1	-0.3	0.0	0.1	-0.1	-4.9
r2	0.5	-19.2	1.4	0.2	0.4	0.1	0.3	0.5	-0.3	0.8	0.2	0.5	0.4	1.0	0.6	0.2	2.7	-17.0
r3	0.3	8.3	-5.3	0.2	0.6	0.2	0.2	0.2	-0.6	0.3	0.1	0.4	0.2	-0.3	-0.4	0.0	-2.2	-8.2
r4	0.0	-0.2	0.4	-1.0	0.1	0.1	0.1	0.1	-0.1	0.1	0.1	0.1	0.0	0.2	0.2	0.2	-0.1	-2.9
r5	0.2	-0.9	0.8	0.1	0.4	0.5	0.3	0.5	-2.5	0.3	0.1	0.6	0.2	0.2	0.2	0.4	5.9	-37.8
r6	0.0	0.4	0.2	0.0	0.2	-1.5	0.1	0.0	-0.4	0.2	0.2	0.1	0.6	-0.2	0.0	0.0	0.4	-5.1
r7	0.1	-0.4	0.4	0.4	0.5	0.6	0.5	0.4	-2.1	0.1	0.0	0.2	0.1	-0.7	0.0	0.3	1.3	-19.5
r8	0.3	4.1	0.5	0.2	0.7	0.6	0.7	-8.3	5.9	0.4	0.2	0.6	0.2	-0.7	0.2	0.3	-3.5	-16.0
r9	-1.3	-2.7	-1.6	-0.5	-5.8	-1.8	-4.4	-3.7	-229.3	-0.3	-0.8	-0.6	-0.4	-7.0	-1.1	-1.9	-355.5	-1150.8
r10	0.1	-0.3	0.0	0.1	0.1	0.3	0.0	0.1	0.0	-3.1	0.0	0.4	0.1	-0.5	0.1	0.1	0.1	-4.5
r11	0.0	-0.2	0.1	0.1	0.3	0.1	0.1	0.2	-1.8	0.1	0.8	0.3	0.1	-0.8	-0.4	-0.1	0.4	-9.4
r12	0.1	2.0	0.1	0.0	0.1	0.0	0.0	0.1	-0.1	0.2	0.9	-1.8	0.2	-1.3	-0.4	0.1	-0.3	-3.8
r13	-0.1	-0.3	0.0	0.0	0.0	0.1	0.0	0.0	-0.5	0.0	0.0	0.2	0.5	-0.5	-0.1	0.0	-0.4	-3.3
r14	-4.4	-21.6	-3.4	-1.0	-10.8	-1.2	-5.9	-3.2	-21.0	-4.2	-6.0	-3.5	-1.1	-218.8	-6.5	-4.7	-179.7	-909.3
r15	-3.4	-20.3	-6.8	-1.6	-7.9	-1.8	-4.1	-3.2	-6.8	-3.8	-3.5	-3.7	-1.6	-9.3	-94.2	-7.1	-180.1	-689.0
r16	-2.7	-2.6	-1.8	-2.7	-4.7	-0.7	-6.1	-1.7	-6.7	-0.5	-1.1	-1.2	-0.4	-3.8	-1.7	-57.5	-111.7	-389.3
Imports	1.3	-17.7	5.4	1.0	10.3	2.5	5.1	5.7	-9.1	3.5	1.0	1.9	0.5	-0.1	-1.0	2.0	0.0	-240.3
Total	-10.2	-72.9	-9.4	-4.6	-15.3	-1.9	-13.0	-12.1	-276.1	-5.9	-7.6	-5.2	-0.2	-243.1	-104.5	-67.6	-822.87	-3511.13

Source: Own calculations

Table 3. Impacts on value added (m€) by region and industry in the Main flooding scenario

	Industries												
	i1	**i2**	**i3**	**i4**	**i5**	**i6**	**i7**	**i8**	**i9**	**i10**	**i11**	**i12**	**Total**
Danube - Direct													
r9	0.00	0.00	-23.24	-28.50	-15.38	-178.07	-1.47	-33.31	-31.99	-44.98	-24.54	-6.20	-387.68
Elbe - Direct													
r14	-4.93	0.00	-38.81	-0.91	-18.80	-69.62	-1.18	-60.63	-58.95	-26.40	-74.93	-24.91	-380.07
r15	-10.87	-0.18	-17.76	-51.71	-7.00	-47.93	-3.66	-30.47	-36.97	-13.94	-41.05	-27.26	-288.80
r16	-1.02	0.00	-7.27	-35.00	-6.58	-32.81	-5.71	-12.45	-9.99	-1.37	-32.04	-4.03	-148.28
Total -Direct	-16.83	-0.18	-63.85	-87.62	-32.38	-150.35	-10.55	-103.56	-105.91	-41.71	-148.02	-56.20	-817.15
Indirect													
r1	-0.11	0.00	0.05	-0.01	0.01	-0.11	0.01	2.59	-0.77	-0.05	-2.13	-4.03	-4.53
r2	-0.04	-0.01	0.06	-0.11	-0.02	-0.08	0.07	5.18	-2.00	-0.23	-7.29	-8.56	-13.02
r3	-0.56	-0.32	0.24	-0.16	-0.22	-0.50	0.03	4.84	-0.57	0.08	-4.25	-5.64	-7.02
r4	-0.01	0.00	0.05	0.01	-0.09	-0.09	-0.04	0.44	-0.19	0.00	-0.66	-1.41	-1.99
r5	-0.24	-0.30	0.11	-0.96	-2.41	-0.96	-0.39	4.99	-3.81	0.29	-10.96	-7.75	-22.39
r6	-0.11	-0.01	0.05	-0.40	-0.17	-0.07	-0.01	0.90	-0.19	0.07	-1.53	-1.88	-3.36
r7	-0.07	0.00	0.25	-0.24	-0.12	-0.26	0.03	4.02	-1.65	-0.06	-10.10	-6.05	-14.26
r8	-0.23	-0.01	-0.05	-0.15	-0.38	-2.42	0.13	6.99	-1.98	0.70	-7.30	-7.00	-11.70
r9	**-1.43**	**0.03**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**-39.98**	**-53.96**	**-95.34**
r10	-0.01	-0.02	0.04	0.00	-0.20	-0.10	-0.07	-0.02	-0.22	0.00	-0.77	-1.41	-2.79
r11	-0.01	0.00	0.12	0.00	-0.01	-0.08	0.03	2.96	-0.28	-0.07	-5.03	-5.30	-7.67
r12	-0.16	-0.05	0.09	0.00	-0.10	0.04	-0.06	1.58	0.00	-0.06	-1.89	-2.93	-3.56
r13	-0.12	0.00	0.07	0.00	-0.02	-0.05	-0.10	0.30	-0.06	0.00	-0.67	-1.63	-2.28
r14	**0.00**	**-0.04**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**-25.28**	**-25.32**
r15	**0.00**	**-0.08**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**-0.08**
r16	**0.00**	**0.04**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**-0.27**	**0.00**	**-11.83**	**-12.07**
Total - Indirect	-3.11	-0.78	1.08	-2.02	-3.73	-4.69	-0.36	34.77	-11.72	0.39	-92.57	-144.65	-227.39

Source: Own calculations

Table 4. Changes in indirect impacts on value-added (m€) from the Main flooding scenario in the Government Aid scenario

	Industries												
	i1	**i2**	**i3**	**i4**	**i5**	**i6**	**i7**	**i8**	**i9**	**i10**	**i11**	**i12**	**Total**
r1	0.08	0.01	0.14	-0.01	0.04	0.02	0.23	1.09	1.64	0.17	2.62	5.60	11.61
r2	0.04	0.02	0.12	0.34	0.00	0.18	0.35	2.08	4.24	0.44	6.38	9.20	23.41
r3	0.35	0.04	0.17	0.04	0.05	0.03	0.53	2.41	2.31	0.35	5.20	9.67	21.15
r4	0.02	0.00	0.05	0.01	0.01	0.12	0.06	0.23	0.65	0.07	0.81	1.76	3.81
r5	0.22	0.08	0.29	-0.22	-0.07	0.23	2.06	2.57	8.27	1.40	11.95	12.69	39.46
r6	0.14	0.00	0.10	-0.10	-0.06	0.27	0.25	0.52	0.89	0.22	1.78	3.36	7.37
r7	0.15	0.00	0.19	-0.03	0.07	0.02	0.61	1.94	4.91	1.16	9.70	10.62	29.32
r8	0.23	0.01	0.16	0.11	0.10	0.09	0.75	4.12	2.93	0.96	7.42	11.65	28.52
r9	**0.50**	**0.06**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**27.65**	**53.96**	**82.17**
r10	0.01	0.02	0.05	0.01	-0.08	0.13	0.09	0.25	0.44	0.10	1.00	1.99	4.02
r11	0.02	0.00	0.01	-0.03	0.02	0.07	0.40	1.17	1.84	0.42	4.48	8.23	16.62
r12	0.15	0.04	0.08	-0.01	0.06	0.06	0.38	0.87	0.91	0.37	2.44	5.06	10.41
r13	0.09	0.00	0.01	0.01	0.01	-0.03	0.09	0.19	0.97	0.09	1.03	2.93	5.39
r14	**0.00**	**0.05**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**25.28**	**25.33**
r15	**0.00**	**0.04**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.04**
r16	**0.00**	**0.02**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.27**	**0.00**	**11.83**	**12.13**
Total - Indirect	2.00	0.41	1.36	0.10	0.16	1.19	5.80	17.43	30.00	6.04	82.45	173.85	320.77

Source: Own calculations

Table 5. Changes in indirect impacts on value added (m€) from the Main flooding scenario in the Business Cycle scenario

	Industries												
	i1	**i2**	**i3**	**i4**	**i5**	**i6**	**i7**	**i8**	**i9**	**i10**	**i11**	**i12**	**Total**
r1	0.02	0.00	-0.10	-0.01	-0.03	0.03	-0.01	-2.59	-0.70	0.02	-2.09	-2.52	-7.99
r2	0.00	-0.01	-0.07	-0.08	0.00	0.02	-0.07	-5.18	-0.88	0.04	-2.65	-2.60	-11.48
r3	0.00	-0.01	-0.24	-0.05	-0.07	0.04	-0.03	-4.84	-1.42	-0.08	-3.56	-5.46	-15.73
r4	0.00	0.00	-0.05	-0.01	0.00	-0.01	0.04	-0.44	-0.16	0.00	-0.38	-0.47	-1.49
r5	-0.03	0.00	-0.27	-0.04	-0.20	-0.03	0.39	-4.99	-2.38	-0.29	-5.19	-6.21	-19.24
r6	-0.02	0.00	-0.07	-0.01	-0.05	-0.06	0.01	-0.90	-0.38	-0.07	-0.96	-1.50	-4.00
r7	-0.02	0.00	-0.25	-0.04	-0.05	0.03	-0.03	-4.02	-1.42	-0.06	-4.18	-4.19	-14.23
r8	-0.03	0.01	-0.23	-0.10	-0.12	-0.03	-0.13	-6.99	-2.17	-0.70	-5.23	-6.92	-22.64
r9	**-0.05**	**-0.03**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**-3.29**	**-3.52**	**-6.89**
r10	0.00	0.00	-0.04	0.00	-0.01	-0.04	0.01	0.02	-0.04	0.00	-0.13	-0.15	-0.38
r11	0.00	0.00	-0.12	0.00	0.01	0.02	-0.03	-2.96	-0.58	-0.05	-2.46	-3.46	-9.65
r12	-0.01	0.00	-0.09	0.00	0.00	-0.04	0.06	-1.58	-0.32	-0.02	-1.20	-1.70	-4.89
r13	-0.02	0.00	-0.07	0.00	-0.01	0.00	0.03	-0.30	-0.13	0.00	-0.34	-0.52	-1.35
r14	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**-1.37**	**-1.36**
r15	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
r16	**0.00**	**-0.04**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.01**	**0.00**	**-0.67**	**-0.70**
Total - Indirect	-0.18	-0.08	-1.60	-0.35	-0.54	-0.06	0.22	-34.77	-10.57	-1.18	-31.66	-41.24	-122.02

Source: Own calculations

Table 7. Comparison of national and regional disaster impact multipliers

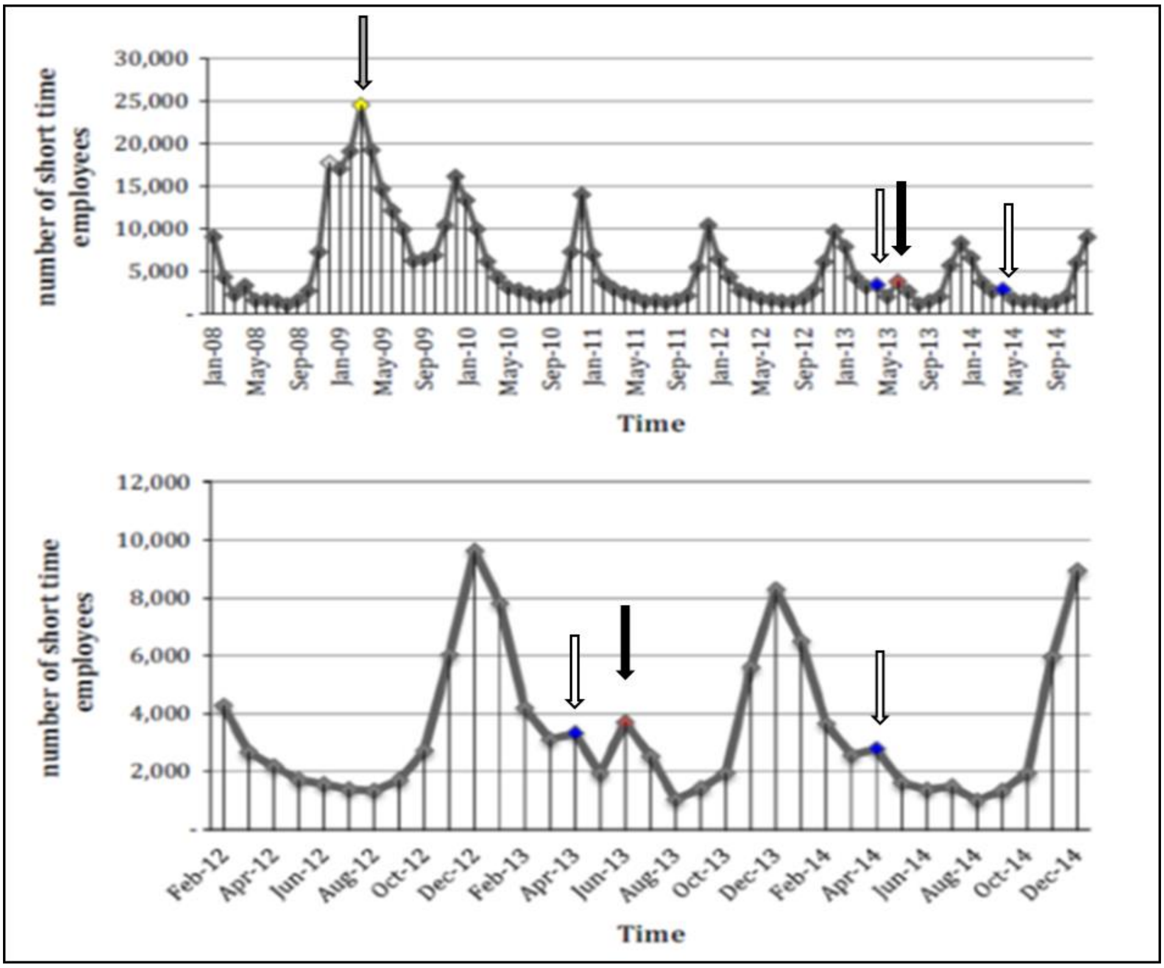
Assumptions		Disaster Impact Multipliers				
		National	r9	r14	r15	r16
Main Scenario	Eq. 1-6	1,110	1,139	1,041	1,000	1,046
Fixed market shares	Eq. 1-6, Eq. 11	1,193	1,306	1,083	1,010	1,057
Fixed trade shares	Eq. 1-6, Eq. 12-13	1,334	1,207	1,176	1,070	1,125
Both shares fixed	Eq. 1-6, Eq. 11-13	1,966	1,588	1,832	1,586	1,420

Source: Own calculations

Figure 1. Set-up of the German use-regionalized multi-regional supply-use table for 2007

		Region 1			**Region r**			RoW	Total
		Products	Industries	Final Demand	Products	Industries	Final Demand		
Region 1	Products		$\mathbf{U}^{11}$	$\mathbf{Y}^{11}$		$\mathbf{U}^{1r}$	$\mathbf{Y}^{1r}$	$\mathbf{e}^{1}$	$\mathbf{g}^{1}$
	Industries	$\mathbf{V}^{1}$							$\mathbf{x}^{1}$
Region r	Products		$\mathbf{U}^{r1}$	$\mathbf{Y}^{r1}$		$\mathbf{U}^{rr}$	$\mathbf{Y}^{rr}$	$\mathbf{e}^{r}$	$\mathbf{g}^{r}$
	Industries				$\mathbf{V}^{r}$				$\mathbf{x}^{r}$
Rest of World			$\mathbf{U}^{RoW1}$	$\mathbf{Y}^{RoW1}$		$\mathbf{U}^{RoWr}$	$\mathbf{Y}^{RoWr}$		$\mathbf{m}^{\bullet}$
Value Added			$\mathbf{W}^{1}$	$\mathbf{0}$		$\mathbf{W}^{r}$	$\mathbf{0}$		$\mathbf{w}^{\bullet}$
Total		$\mathbf{g}^{1}$	$\mathbf{x}^{1}$	$\mathbf{y}^{1}$	$\mathbf{g}^{r}$	$\mathbf{x}^{r}$	$\mathbf{y}^{r}$	$e^{\bullet}$	

Figure 2. Number of undertime employees in Germany. *Top panel*: Monthly time series from January 2008 to December 2014. *Bottom Panel*: Enlargement of top panel from February 2012 to December 2014



Source: Schulte in den Bäumen et al. 2015, Federal Labour Office.

Figure 3. Germany's 16 Federal States, their percentage shares in national population and GDP, and percentage inoperability of directly affected regional industry output

Number	Federal State	Share in Population	Share in GDP	Inoperability
1	Schleswig-Holstein	3.4%	3.0%	-
2	Hamburg	2.1%	3.4%	-
3	Niedersachsen	9.7%	8.5%	-
4	Bremen	0.8%	1.1%	-
5	Nordrhein-Westfalen	21.9%	21.8%	-
6	Rheinland-Pfalz	4.9%	4.3%	-
7	Hessen	7.4%	8.8%	-
8	Baden-Württemberg	13.1%	14.7%	-
9	**Bayern**	15.2%	17.9%	0.13%
10	Saarland	1.3%	1.2%	-
11	Berlin	4.1%	3.5%	-
12	Brandenburg	3.1%	2.2%	-
13	Mecklenburg-Vorpommern	2.1%	1.4%	-
14	**Sachsen**	5.1%	3.9%	0.51%
15	**Sachsen-Anhalt**	3.0%	2.3%	0.72%
16	**Thüringen**	2.8%	2.0%	0.40%

Source: VGR der Länder

[1] The model was implemented in GAMS and solved via CONOPT3. The computation time varied from scenario to scenario, but was generally less than one hour.

[2] The majority of labour contracts in Germany specify a fixed number of working hours for a certain monthly salary (apart from overtime hours). Due to this, cases of stark underutilization of labour inputs, e.g. due to a disaster, put danger on the survival of affected firms, since workers have to be paid nonetheless. In order to prevent insolvencies of actually viable companies due to external events, firms can apply for what we will call *undertime* allowances (in German: *Kurzarbeit*), which allow them to pay their workers only for the hours worked, while the unemployment insurance pays two-third of remaining contractual salary.

3 Estimates of the direct economic losses are lacking in Koks et al. (2015). Hence, we cannot compare our disaster multipliers with theirs. We can only compare the differences in the total economic losses´ estimates.