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Quantifying the consequences of disturbances on wood revenues with Impulse Response Functions

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Abstract

Forest disturbances in Europe are very likely to increase in frequency and intensity. Assessing their economic consequences is required to identify feasible adaptation strategies. Such economic calculations depend on estimates for the reduction in revenues after disturbance events. These losses can be caused by both a lower wood quality as well as an oversupply on the wood markets. Despite its importance, data-driven approaches to quantify the consequences of disturbances on wood revenues in Central Europe are rare. We applied econometric time series analysis with Structural Vector Autoregressive (SVAR) models to harvest and sales data from Hesse, Germany. Additionally, we derived estimates for reductions in wood revenues for integration in bioeconomic simulation models. Our analyses indicate that the observed losses in wood revenues for spruce after disturbances are mainly due to an oversupply on the wood markets, rather than a loss in wood quality. In addition, the results suggest that calamities of transregional extent or multiple disturbances in subsequent years are likely to reduce wood revenues beyond the assumptions often used in bioeconomic simulation models. Although our results for beech were more ambiguous, they indicate that losses in revenues for beech after disturbances in the past were mainly due to a reduced wood quality. Our study highlights the importance of taking a differentiated view on the consequences of disturbances on wood revenues, considering their spatial extent and species-specific mechanisms.

Keywords:

- Timber price fluctuation
- Wood market
- Wood assortments
- Impulse Response Function
- Disturbance economics
- Extreme events

1 Introduction

In the years 2018-2020, Central European forests suffered from a sequence of storm and drought events. This period of disturbances resulted in unprecedented forest damages, with 277,000 ha having to be reforested in Germany alone (Bundesministerium für Ernährung und Landwirtschaft, 2021). The economic consequences for forest enterprises were estimated to exceed 12.7 billion Euros (Möhring et al., 2021). Such disturbance events clearly underline the need for an ecological and economic transition of Central European forests (Schuldt et al., 2020). Identifying adaptation strategies, which also allow forest enterprises to buffer the economic consequences of climate change, will be key to such a transition.

Bioeconomic modeling has proven helpful in assessing the economic impacts of climate change on forestry (e.g. Paul et al., 2019; Thiele et al., 2017) and in the identification of suitable adaption strategies (e.g. Fuchs et al., 2022; Möllmann & Möhring, 2017; Müller et al., 2019). Such models usually require estimates for occurrence probabilities and economic consequences of disturbances. Regarding the associated tree mortality, Staupendahl (2011) developed an estimation approach, which has recently been improved by Brandl et al. (2020), and Senf and Seidl (2021a) described the forest disturbances regimes based on remote sensing. However, capturing the adverse economic consequences of forest disturbances is still challenging. They incorporate three main aspects: Potential increases in harvest costs, decreases in wood revenues, and long-term consequences due to the suboptimal timing of the harvest. Our study focuses on revenues as we found a considerable lack of empirical studies that estimate the impacts of disturbances on wood revenues in Central Europe. In the North American forestry literature, several econometric studies have addressed the effects of disturbances, such as the Hurricanes Hugo (Prestemon & Holmes, 2000; Yin & Newman, 1999) and Katrina (Sun, 2016), or the Biscuit fire (Zhai & Kuusela, 2020), on market prices. Since such econometric estimates were not available for Central Europe, previous simulation studies on impacts of and adaptation to climate change estimated the reduction in wood revenues due to disturbances based on expert knowledge. For example, Dieter (2001) assumed a reduction of 50 % for the net revenues of spruce and beech, which seemed plausible when compared to wood prices after a storm in 1990. However, Staupendahl and Möhring (2011) assumed a reduction of only 30 %, while Knoke et al. (2021) even assumed negative net revenues for extreme disturbance events. Möllmann and Möhring (2017) quantified reductions in wood revenues based on a survey of forest managers and owners and found that storm events reduced the revenues of conifers by 15.2 % and those of deciduous species by 21.3 %.

Therefore, this study seeks to quantify the impacts of disturbances on wood revenues based on data from a forest enterprise. This should provide empirical estimates for future simulation models.

Bioeconomic simulations usually require an estimation of the magnitude of reduction in wood revenues. However, a deeper understanding of the underlying mechanisms may allow for a more thorough assessment of the economic impacts of disturbances. The average revenue per cubic meter wood depends on the composition of the wood assortments sold (several products) and on the market prices of the distinct assortments. We hypothesize that disturbances alter the average revenue in two ways: firstly, through quality losses, which alter the assortment composition, and secondly, through lower market prices caused by higher wood supply. Disturbances lead to biophysical wood damages, such as broken logs, boreholes from insects, or secondary fungal infestations. These damages reduce the wood value since the share of high-value timber can be expected to be reduced. For instance, Loeffler and Anderson (2018) found that infestations by mountain pine beetles in the US reduced the sawlog volume by 15 %, increasing up to 50 % in advanced attack stages. We refer to this effect as the "quality effect". Additionally, large disturbances lead to an extraordinary high wood supply due to salvage activities (see e.g. Toth et al., 2020). This supply can be considered highly inelastic to price changes (e.g. Marsinko et al., 1996; Prestemon & Holmes, 2008). Consequently, the market prices will fall in the short run (e.g. Prestemon & Holmes, 2000; Yin & Newman, 1999) and therefore, also the average wood revenue. We refer to this effect as the "market effect". Potential long-run effects of disturbances, such as a future reduction in wood supply due to reduced wood stocks (e.g. Prestemon & Holmes, 2000) were out of the scope of our analysis. Distinguishing between quality and market effect is important for investigating the spatial effects of disturbances. In contrast to regularly occurring minor disturbances, large-scale events affecting entire enterprises or regions would influence not only the wood quality but also the wood markets.

The quality effect could be quantified by standard regression analyses of wood damages on the corresponding revenues. In contrast, the market effect may require more advanced methods from the field of time series analysis, due to time lags in the market responses. It is, for example, likely that a higher wood supply reduces revenues with a certain delay, due to already signed contracts (see Möhring et al., 2021), and that the effect lasts longer since market prices are also lower in the following years.

Previous studies that applied time series analyses in forestry are, for example, Alavalapati et al. (1997), who assessed the influence of exchange rates and the U.S. pulp price on Canadian pulp price, and Hetemäki et al. (2004) as well as Kolo and Tzanova (2017), who forecast wood exports. Time series analyses have been used to study the impacts of policy decisions on wood markets, e.g., regarding trade restrictions (Baek & Yin, 2006) or protection of species (Yin, 2001). Kożuch and Banaś (2020) studied relations between Central European markets for beech round wood and Fuhrmann et al. (2021) those between prices of round wood and products of wood industry. Most applications of time series analyses in forest economics have focused on market prices and the trade of wood products. In contrast, our study targets the level of large forest enterprises. In this context, identifying the effects of forest disturbances on actual wood revenues, which also consider changes in wood quality, is more informative than studies limited to the effects on market prices.

Empirical analyses of operational data, such as book-keeping data and forest management records, can be challenging since these are not collected and structured for scientific questions and methods. However, operational data can better reflect the impact of disturbances on the revenues of single forest enterprises than government statistics can. The latter usually aggregate data from several enterprises and experience significant averaging effects. Thus, analyses based on such statistics are likely to underestimate the impact at the enterprise level. In this study, we contribute by estimating quality and market effects of disturbances based on harvest and sales records from HessenForst, the public forest service of the Federal State of Hesse in Central Germany, which manages a forest area of 326,320 ha (Thünen-Institut, 2015). This data base is representative for single large forest enterprises, but also provides a sufficient number of harvest and sale records from years influenced by disturbances. Based on this data, we derive the share of damaged wood, as an indicator for wood quality, the harvest volume, as an indicator for wood supply, and the average revenue per cubic meter wood.

We use Vector Autoregressive (VAR) models to investigate the dynamics between wood revenues and harvest volume as well as the share of damaged wood. Within the VAR framework, we test for Granger Causality to infer which variable is better suited to predict revenues. We further adopt the well-established tool of structural VAR (SVAR) models (Sims, 1980) to determine the consequences of hypothetical shocks (disturbances) to the harvest volume or the share of damaged wood on wood revenues. In the SVAR framework, causal investigations are performed by tracing out the effect of such exogenous structural shocks in one of the variables (*ceteris paribus*) on the other variables in the system using Impulse Response Functions (IRFs) (see Lütkepohl, 2007). The underlying structural shocks are mutually uncorrelated and have a clear economic interpretation. The suitability of SVARs to infer the causal relationships in commodity markets was, among others, demonstrated by Dalheimer et al. (2021), who analyzed how oil-supply shocks affect the prices for corn in Sub-Saharan African countries.

Examples of SVAR and IRF applications in forest research include: Linden and Uusivuori (2002), who assessed the response of wood markets in Finland to negative supply shocks due to forest conservation measures, and Zhou and Buongiorno (2006), who estimated the transmission of local supply shocks to neighboring markets. Compared to intervention analysis, as often applied in the context of forest disturbances, where a dummy variable describes the effects of a single disturbance event (e.g. Prestemon & Holmes, 2000; Yin & Newman, 1999; Zhai & Kuusela, 2020), our approach with SVARs allows for a detailed and continuous description of disturbance characteristics. We disentangle the effects of higher wood supply and lower wood quality on a continuous scale and additionally include a dummy variable, similar to intervention analysis, for transregional calamity events. Lemoine (2021) highlighted an additional advantage of IRFs for estimating the consequences of disturbances to ecosystems. Since IRFs allow for the standardization of shocks and responses, the estimated disturbances can be easily compared across scientific studies. IRFs are therefore a promising method for estimating the reduction in wood revenues after disturbances. Such standardized results, compared to results referring to a specific historic event, are particularly useful for future, more general applications in bioeconomic models. However, IRFs have rarely been applied in the corresponding literature.

Applying econometric methods, our study seeks to disentangle the effect of quality losses and market reactions for the two economically most important species in Germany: Norway spruce (*Picea abies* (L.) KARST) and

European beech (*Fagus sylvatica* L.). As a novel feature, we calculated IRFs with different shock intensities to analyze disturbances of varying severity. The analyses are guided by the following research questions *Q1-Q5*:

Q1: Are decreasing revenues predominantly reasoned by higher shares of damaged wood (quality effect) or by higher wood supplies (market effect) and is this effect consistent across the two species?

Q2: Do transregional disturbances further decrease revenues?

Q3: By what order of magnitude and in which time horizon do revenues decline after disturbances of varying severity?

Q4: By what order of magnitude and in which time horizon do sequential disturbances decrease revenues?

Q5: How can the econometric results be applied in future bioeconomic simulation models?

Thus, our study contributes to a more sophisticated understanding and modeling of the direct economic consequences of disturbances by distinguishing between species and the extent and severity of the disturbance event, as well as by estimating the development of revenues in the years following the event.

2 Method

2.1 Data

We used operational data from the public forests of Hesse, managed by HessenForst, the public forest service of the Federal State of Hesse, Germany. In 2012, the Hessian public forest was composed of 34 % European beech, 21 % spruce, 10 % oak, 10 % pine, and 22 % other species or open areas, covering altogether 326,320 ha of forest land (Thünen-Institut, 2015). The Hessian forests extend over the German low mountains as well as the Rhine-Main plain and are located in Central Germany. The public forests of Hesse supplied about 40 % of the harvested wood of European beech as well as Norway spruce in Hesse between 2002 and 2012 (Thünen-Institut, 2015). It can be expected that HessenForst's wood sales will have a considerable impact on Hessian markets and that disturbance-induced increases in harvest volumes are representative of the entirety of Hesse. The forests' stocks and harvest volumes are almost in line with the average of all federal forests in Germany as well as the German average (Thünen-Institut, 2015). The species composition differs notably only by a higher share of beech and a lower share of pine (Thünen-Institut, 2015). We thus consider the analyzed data and most of the related wood supply chains to be representative for other public enterprises and also for large private enterprises.

We used two distinct operational data bases of HessenForst, the annual harvest records ($48,258$ entries for spruce and beech) and the annual sales records ($620,706$ entries for spruce and beech). Both were available for the years 2005-2020 for 41 forestry districts (ranging from $1,700$ to $21,600$ ha, with 8,400 ha on average). The harvest data contained the volume of harvested wood and whether it was a salvage harvest ("damaged") or not. The sales data contained information about the sold volumes by wood assortments (defined by dimension and quality[1]), the respective revenues, and the types of sale[2].

Our study considers the two most abundant species, Norway spruce and European beech, as examples of a coniferous and a deciduous species, respectively. We compiled three time series for both species (Fig. 1): Based on the harvest records, we calculated (i) the total harvest volume in each year and (ii) the annual share of damaged wood, including damages by abiotic, biotic, and unknown disturbance agents. Based on the sales records, we calculated (iii) the annually averaged wood revenues. By "revenues" we refer to the average observed revenues earned by HessenForst per cubic meter of wood that was actually sold in the respective year, before subtracting harvest costs. Specifically, we calculated the averaged revenues across all assortments per year, weighted by the actual shares of the assortments. In contrast, "prices" refer to market prices of specific wood assortments and, by definition, do

[1] The assortment classification distinguishes between sawlogs and pulpwood (Supplements A.VII, B.VI). For sawlog assortments, quality classes from A to D (where A is the highest quality) and dimension classes (diameter in the middle of the log) are defined. In 2015, a new master agreement on roundwood classification was introduced in Germany (RVR, Deutscher Forstwirtschaftsrat e.V. & Deutscher Holzwirtschaftsrat e.V., 2020), but the actual assortment criteria depend on the potential wood buyers. In the period analyzed, a trend can be observed, for example, from the sale of separate qualities (e.g. B and C) to mixed qualities (e.g. B/C). Since we refer to averaged revenues across all assortments and not to the prices of individual assortments, changes solely related to this classification can be considered to be of minor importance for our results.

[2] We considered roadside sales, wood out of storage (wet and dry), auctions and submissions. We added the value of the harvest costs, based on the model of von Bodelschwingh (2018), to revenues from stumpage sales (about 15 % of the total volume sold) in order to homogenize the types of sale.

not take into account disturbance-induced changes in wood quality. We used nominal values as reported by HessenForst.

We normalized harvest volumes and revenues to the base year 2013, which is in the middle of the time series and not directly affected by exceptional disturbances, "calamities" (Fig. 1, detailed calamity definition below). 100 % thus refers to a situation without such large disturbances. This relative formulation provides a direct interpretation of the magnitude of changes in revenues compared to the change in harvest volumes due to disturbances and can be easily transferred and compared to other situations or regions. The share of harvested wood recorded as damaged was not normalized. It is by construction limited to 0-100 % since it is calculated as the harvest volume recorded as damaged divided by the total harvest volume in the year.

A common problem using operational data from forest enterprises is that the harvested wood from a specific harvest activity cannot be directly related to its sale. In contrast to harvest records, sales data refer to wood assortments. Assortments of one harvest activity may be sold to different clients at different points in time and may also be combined with wood from other harvest activities. Especially in calamity years, the resulting time lag between harvest and sale can become exceptionally long. Therefore, for our study, we lacked a direct connection between harvest volume or share of damaged wood and revenues. Hence, if the year was not a reliable identifier for both data sets – since harvest and sale of the same wood may occur in different years – classical regression analyses would not be applicable. In a lag-order selection between harvest and sale volumes, we clearly rejected the null hypothesis of no inter-annual time lag between harvest and sale of wood, for both spruce

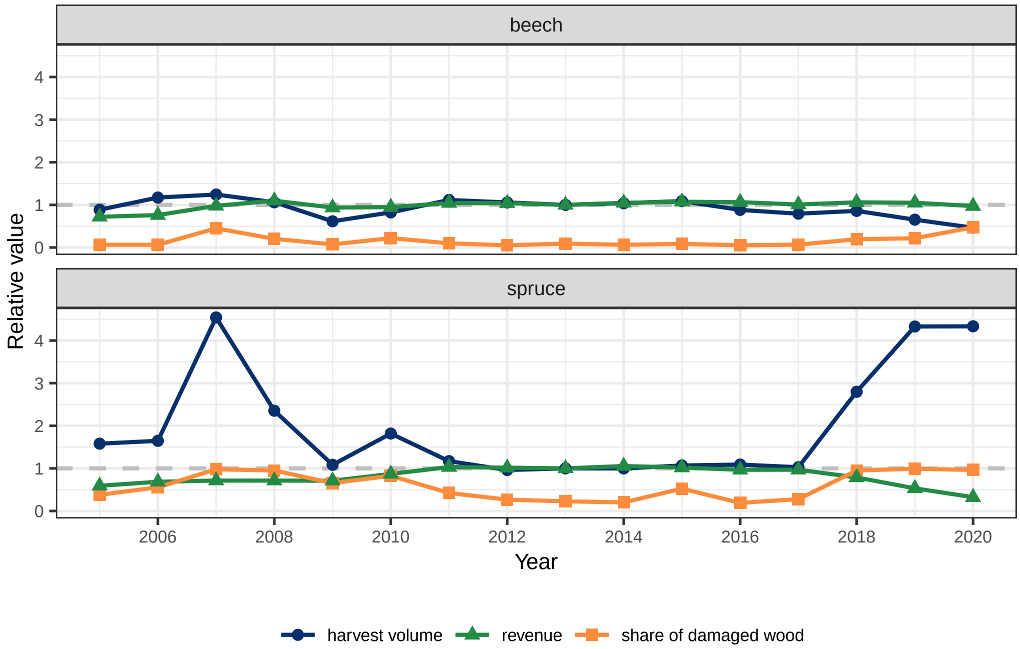

Figure 1: Time series harvest volume, share of damaged wood and wood revenue (per cubic meter wood) in the Hessian public forests from 2005 to 2020. Harvest volume and wood revenue are expressed as indices with a non-calamity base year in the middle of the time series (2013 = 100 %). The share of damaged wood is the annual proportion of damaged wood volume in the total harvest volume.

and beech (Supplements A.I.1 and B.I.1). Consequently, we applied time series models that explicitly consider time lags between the variables. We applied methods of VARs, SVARs and IRFs using the `R` (R Core Team, 2020) packages `vars` (Pfaff & Stigler, 2018), and `tseries` (Trapletti et al., 2020).

2.2 Model estimation

For research questions *Q1-Q4*, we estimated two separate VARs for each species. We first modeled the relationships between revenues and harvest volumes and then distinctly the relationships between revenues and shares of damaged wood. Due to the limited lengths of the time series, we did not consider a complex model that combines all three series in one VAR. The VARs were the basis for all further analyses.

For *Q1*, we conducted unidirectional Granger Causality tests (Granger, 1969) between revenues and the harvest volume, as an indicator of wood supply, and the share of damaged wood, as an indicator of wood quality. We conducted separate Granger Causality tests for the harvest volume and for the share of damaged wood to ensure that the influences of each variable on revenues could definitely be attributed to that variable. This indicated whether the revenues change mainly due to the market or due to the quality effect. For *Q2*, we implemented a dummy variable *calamity* for years with transregional calamities in the VARs and directly interpreted the estimated coefficient. For *Q3* and *Q4*, we calculated SVARs from the reduced-form VARs to evaluate the model dynamics under erratic shocks of the harvest volume or the share of damaged wood by means of IRFs. In order to support the application of our findings in future simulation studies (*Q5*), we interpreted the econometric results under consideration of possible limitations in the observed data and proposed aggregated reduction factors (Section 4). Since simulation studies often refer to losses in net revenues, we enriched our IRF analyses of gross revenues with estimates for increases in harvest costs. The proposed assumptions were consistently derived for Hessian conditions, but were based on expert knowledge and recent experience of HessenForst rather than on econometric analyses.

Q3 and *Q4* required the modeling of the response of revenues to changing harvest volumes, respectively shares of damaged wood. The applied IRFs require the dynamic structural form of a VAR. An SVAR of order p can generally be expressed in the form

$$By_t = Cx_{t-1} + \epsilon_t, \quad \epsilon_t \sim (0, \Sigma_\epsilon), \tag{1}$$

with $y_t = (y_{1,t}, ..., y_{K,t})'$ as a vector of K observed time series variables and B as a $(K \times K)$ matrix summarizing the contemporaneous structural relations between the time series variables. The vector x_{t-1} contains a constant and p lags of y_t ($x'_{t-1} = (y'_{t-1}, ..., y'_{t-p}, 1)'$) and C is a $(K \times (Kp + 1))$ matrix of lagged structural coefficients. ϵ_t is a vector of uncorrelated, structural error terms with a diagonal covariance matrix Σ_ϵ (see e.g Lütkepohl, 2007, for a detailed description of the structural model).

In this study, we were interested in analyzing the linkages between revenues b_t and one explanatory variable a_t (the harvest volume or the share of damaged wood), i.e. we estimated a bivariate model ($K = 2$) with $y_t = (a_t, b_t)'$. Therefore, the general form (Equation 1) can be specified to

$$\begin{pmatrix} 1 & -\beta_{ab} \\ -\beta_{ba} & 1 \end{pmatrix} \begin{pmatrix} a_t \\ b_t \end{pmatrix} = Cx_{t-1} + \epsilon_t. \tag{2}$$

Solving for a_t and b_t yields the following structural model:

$$a_t = \beta_{ab} b_t + c'_1 x_{t-1} + \epsilon_{1t}, \tag{3}$$

$$b_t = \beta_{ba} a_t + c'_2 x_{t-1} + \epsilon_{2t}. \tag{4}$$

Equation 4 models the determinants of revenues with the contemporaneous effect of wood supply (or wood quality) given by β_{ba}. For instance, a negative shock ϵ_{1t} represents a shift in the wood supply curve that leads to a higher available wood supply on the market and may be caused, for example, by a calamity.

Since the required structural form cannot be recovered directly from the data, we first had to estimate the model in the reduced-form representation. It is obtained by pre-multiplying B^{-1} to Equation 1 such that y_t only depends on its own history

$$y_t = Ax_{t-1} + u_t, \quad u_t \sim (0, \Sigma_u), \tag{5}$$

where $A = B^{-1}C$ is a matrix containing the autoregressive parameter and intercept terms and $u_t = B^{-1}\epsilon_t$ is a vector consisting of reduced-form error terms with a non-diagonal covariance matrix Σ_u. Equation 5 thus allows for cross-equation correlations of the residuals u_t. Nevertheless, the VAR parameter can be estimated consistently via least squares or maximum likelihood methods (Lütkepohl, 2007).

After estimation of the reduced-form VAR, the structural parameter of the SVAR can be obtained by pre-multiplying the matrix B to the estimated version of Equation 5, where $\Sigma_u = B^{-1}(B^{-1})'$.[3] The SVAR models are thus conditioned on the residuals of the reduced-form VAR, which means that the main objective of the reduced-form VAR in our analyses is to provide consistent estimates of the residuals.

[3] A simplifying standardization often made during estimation is that the covariance matrix of the structural shocks is equal to an identity matrix $\Sigma_\varepsilon = I_K$.

The general issue in SVAR analysis is that the structural form is under-identified (Lütkepohl, 2007). In our study, there are 4 parameters in B^{-1}, but the reduced-form covariance matrix only provides $K(K+1)/2 = 3$ restrictions in the form $0 = \text{vech}(\Sigma_u) - \text{vech}(B^{-1}(B^{-1}))$. Therefore, we had to add one additional restriction to the system.

A common approach in the SVAR literature is to restrict one short-run parameter in B (Kilian & Lütkepohl, 2017; Sims, 1980). The assumption behind the restriction is that not all variables are affected by an immediate feedback. We implemented the restriction $\beta_{ab} = 0$, implying that the harvest volume responds to changes in revenues with a delay of at least one year. This restriction appears reasonable for two reasons: Firstly, it is unlikely that forest enterprises would immediately adopt their short-term operational planning to changing wood prices. Secondly, this parameter played a minor role in our study, as we do not elaborate the response of revenues on the harvest volume or on the share of damaged wood.

In order to describe possible effects of extraordinarily large disturbances not confined to Hesse relative to undisturbed years, we identified years with transregional disturbances, referred to as "calamities". We included a dummy variable for these years in the reduced-form VAR, which enabled us to calculate distinct intercept terms for years with and without such events. The formulation is similar to a pulse variable in previous intervention analyses (see e.g. Prestemon & Holmes, 2000; Yin & Newman, 1999; Zhai & Kuusela, 2020), but the dummy variable decoded multiple events in the time series. We considered only immediate, no lagged, effects of this variable. We interpreted the resulting difference between the intercepts as the additional effect of transregional calamities on revenues (*Q2*). We assumed that negative effects of such events can go beyond the effects of an increased harvest volume or share of damaged wood in Hesse since, e.g., the processing, transporting, or storage capacities are limited and the industry cannot acquire the entire available wood volume. This could additionally decrease the revenues due to over-proportionally decreasing market prices. We defined “calamity year” as a year in which the total harvested volume of all species across Germany exceeded the long-term German mean plus the standard deviation. According to Genesis online (Federal Statistical Office Germany (Destatis), 2021), covering 1998-2020, the years 2007 (storm Kyrill) as well as 2019 and 2020 (bark beetle outbreaks after storm Friederike in 2018 and a severe drought) were such calamity years with $calamity = 1$ ($calamity = 0$ otherwise).

Usually, the impulse in IRFs amounts to one standard deviation of the impulse variable (Lütkepohl, 2007). For *Q3*, we defined different shock intensities, i.e. magnitudes of the impulse, in order to simulate disturbance events of varying severity. This was done by re-scaling the contemporaneous structural relations in B^{-1} in relation to the harvest volume. The resulting matrix R relates the impulse to the harvested wood in the reference year 2013 and thus enables shock estimations of varying intensities by multiplying the column with $shock.intensity$:

$$R_{1*} = \frac{B^{-1}_{1*}}{B^{-1}_{11}} \cdot shock.intensity. \tag{6}$$

Since the impulse variable is the normalized harvest volume, a $shock.intensity$ of 1 means, for example, that the harvest volume shock is as high as the harvest volume in 2013. Thus, the total harvest volume is twice as high as in a year without transregional calamities. The IRFs for the share of damaged wood were calculated similarly, but refer to an increase in the share of damaged wood in percentage points.

For *Q4*, we calculated revenue responses to multiple disturbances in subsequent years by adding the responses, shifted by one year. For example, shocks in 2 subsequent years were calculated as $b_1^r = b_1, b_2^r = b_2 + b_1, b_3^r = b_3 + b_2, \ldots$.

3 Econometric results

Our results indicate that the effects which reduce wood revenues after disturbances are different for spruce and beech.

3.1 Identifying covariates influencing wood revenues (*Q1-Q2*)

We estimated VAR models for wood revenues dependent on the harvest volume and the share of damaged wood. The comparison of the estimated VARs and the Granger Causality analyses suggested that the revenues of spruce and beech are explained by different covariates.

3.1.1 Spruce

Our results suggest that the harvest volume is better suited than the share of damaged wood to explain the development of spruce revenues.

We applied the four most common lag-order selection procedures to find the model that best balances complexity and accuracy (Supplement A: Tab. 3 and 6). The model selection suggested VARs with a time lag of 2 years and a dummy variable for calamity years. Regarding *Q1*, we were mainly interested in the cross-variable effects between the revenues and the harvest volumes and between the revenues and the share of damaged wood (Tab. 1, for the full model summaries see Supplement A). We investigated these cross-variable effects separately for each model and compared the distinct results.

Firstly, we compared the *adj.* R^2 of the models, which both indicated relatively good fits. With an *adj.* R^2 of 0.88, the VAR of the revenues and the harvest volume was slightly better than the VAR with the revenues and the share of damaged wood (0.83, Tab. 1). The Granger Causality test further supported this finding. It tests the null hypothesis that the respective covariate does not Granger-cause revenues. With a p-value of 0.12, the hypothesis of a non-causal relationship between harvest volumes and revenues is more likely to be rejected than between the shares of damaged wood and revenues (p-value of 0.62). Although the null hypothesis cannot be rejected at any conventional significance level, the remarkable difference in p-values reinforces the aforementioned tendency that the revenues of spruce are mainly influenced by the harvest volume (market effect), whereas there is no evidence for a strong relationship between revenues and the share of damaged wood (quality effect).

We further corroborated this finding by incorporating all three time series in one VAR (Supplement A.V), which confirmed that revenue changes are mainly explained by the harvest volume, our indicator for wood supply. The coefficients of the relationship between revenues and harvested volumes were only slightly altered compared to the VAR considering only the harvest volume. The share of damaged wood thus did not improve the model considerably and reduced the *adj.* R^2. Based on these findings, and due to the limited degrees of freedom in the VAR with all three time series[4], we build all following analyses on the harvest-volume model.

Regarding *Q2*, we were interested in the influence of the calamity dummy variable. The model selection procedure (Supplement A: Tab. 3) confirmed

[4]For the IRFs based on the VAR that includes all time series, we refer the reader to Supplement A.V. One should bear in mind the limitations of this model, which nevertheless provides the same conclusions as the harvest-volume model.

Table 1: Estimated coefficients of the VAR models describing the wood revenues of spruce dependent on the harvest volume or share of damaged wood. Harvest volumes and revenues are expressed in relation to the non-calamity year 2013. const: intercept term, calamity: dummy variable for calamity years, l1,l2: the variable is lagged by 1-2 years, respectively.

Coefficient	Estimate	Standard Error
Model 1: effect of harvest volume (adj. $R^2 = 0.88$)		
harvest volume, l1	-0.054	0.027
revenue, l1	0.695	0.388
harvest volume, l2	-0.040	0.031
revenue, l2	-0.526	0.224
const	0.902	0.328
calamity	-0.202	0.077
Model 2: effect of share of damaged wood (adj. $R^2 = 0.83$)		
share of damaged wood, l1	-0.127	0.134
revenue, l1	1.184	0.405
share of damaged wood, l2	0.039	0.123
revenue, l2	-0.650	0.260
const	0.459	0.399
calamity	-0.134	0.092

the relevance of the calamity dummy variable, which had a considerable negative effect on wood revenues (Tab. 1: model 1). Thus, in years with transregional calamities, wood revenues were estimated to be additionally reduced by 20.2 %-points.

3.1.2 Beech

In the case of beech, the VAR using the share of damaged wood to predict revenues achieved a higher explanatory power than the VAR based on the harvest volume. However, the estimated VARs for beech showed less signals than those for spruce, since all 3 time series of beech appeared to have a lower volatility in their historic development (Fig. 1).

Our model selection procedure (Supplement B: Tab. 3 and 5) suggested VARs with a time lag of up to 3 years and a dummy variable for calamity years. Similar to spruce, the VARs differed in their explanatory power (Tab. 2). However, for the beech revenues, the share of damaged wood appeared to be more important. The *adj.* R^2 was 0.58 for the VAR with the harvest volume and 0.82 for the VAR with the share of damaged wood. This trend was supported by the Granger Causality test, $p = 0.285$ for the harvest volume and $p = 0.015$ for the share of damaged wood. This indicated the relative importance of the share of damaged wood (quality effect) compared with the harvest volume (market effect).

The model incorporating all 3 time series (Supplement B.V) supported these findings. Among the VARs with harvest volume, share of damaged wood and a combination of both, the model using only the share of damaged wood reached the highest *adj.* R^2. The estimated coefficients were less stable compared to the spruce models. However, this might be related to the limitation that a maximum lag order of 2 years could be considered when combining all 3 time series, while a lag order of up to 3 years was chosen for the separate VARs in Tab. 2. In summary, the analyses indicated that it is most likely that the beech revenues are mainly related to the share of damaged wood (quality effect) rather than the harvest volume (market effect).

Although the model selection suggested the integration of the dummy variable for calamity years, its effect remained much smaller than in the spruce model (Tab. 2: model 4, compared to Tab. 1: model 1).

Table 2: Estimated coefficients of the VAR models describing the wood revenues of beech dependent on the harvest volume or share of damaged wood. Harvest volumes and revenues are expressed in relation to the non-calamity year 2013. const: intercept term, l1,l2,l3: the variable is lagged by 1-3 years, respectively.

Coefficient	Estimate	Standard Error
Model 3: effect of harvest volume (adj. $R^2 = 0.58$)		
harvest volume, l1	0.165	0.166
revenue, l1	-0.179	0.372
harvest volume, l2	0.118	0.144
revenue, l2	-0.477	0.357
harvest volume, l3	-0.013	0.088
revenue, l3	0.540	0.231
const	0.900	0.258
calamity	0.022	0.048
Model 4: effect of share of damaged wood (adj. $R^2 = 0.82$)		
share of damaged wood, l1	-0.209	0.187
revenue, l1	-0.125	0.346
share of damaged wood, l2	-0.285	0.080
revenue, l2	-0.415	0.195
share of damaged wood, l3	-0.165	0.129
revenue, l3	-0.003	0.136
const	1.662	0.487
calamity	0.003	0.031

3.2 Responses of wood revenues to disturbance impulses (*Q3-Q4*)

Based on the VARs, we calculated SVARs and IRFs to investigate the effects of exogenous shocks. We interpreted the influence of these shocks on wood revenues as the consequences of biophysical disturbances. Thus, the varying intensities of the shocks in harvest volume or share of damaged wood are interpreted as disturbances of varying severity. In addition to this, we simulated how multiple disturbances in subsequent years would influence wood revenues for spruce in our IRF framework.

3.2.1 Spruce

The Granger Causality test identified the harvest volume as a key covariable in the estimation of spruce revenues. We thus focused on IRFs with shocks in the harvest volume to quantify the effect of disturbances. A shock twice as high as in a non-calamity year (shock intensity 1) already led to a decrease in wood revenues by about 12 % in the year of the disturbance (Fig. 2a, Tab. A1). This effect persisted in the two subsequent years (about 14 % and 10 %) and subsided in the third year. The decrease in revenues linearly increased with the shock intensity (compare Fig. 2a from upper to lower panel) and reached up to 41 % for a shock intensity of 3. The highest supply in the observations corresponded to a shock intensity of 3.54 (storm Kyrill in 2007, Fig. 1), which would cause a decrease in revenues of 43 % in the same and 49 % in the following year. In the case of calamity events, which also affect transregional wood markets, the decrease in wood revenues for a shock intensity of 3 would be $36\,\% + 20\,\% = 56\,\%$, i.e. the sum of the IRF (Fig. 2a) and the estimated calamity dummy variable (Tab. 1: model 1).

We further used the IRFs to simulate a series of years with disturbances in direct succession (Fig. 2b) comparable to situations such as in the years 2018-2020 in Hesse (Fig. 1b). The results suggested that for single disturbances none of the simulated shock intensities reduced revenues by $> 50\,\%$. In contrast, for multiple shocks in subsequent years, such high losses in revenues

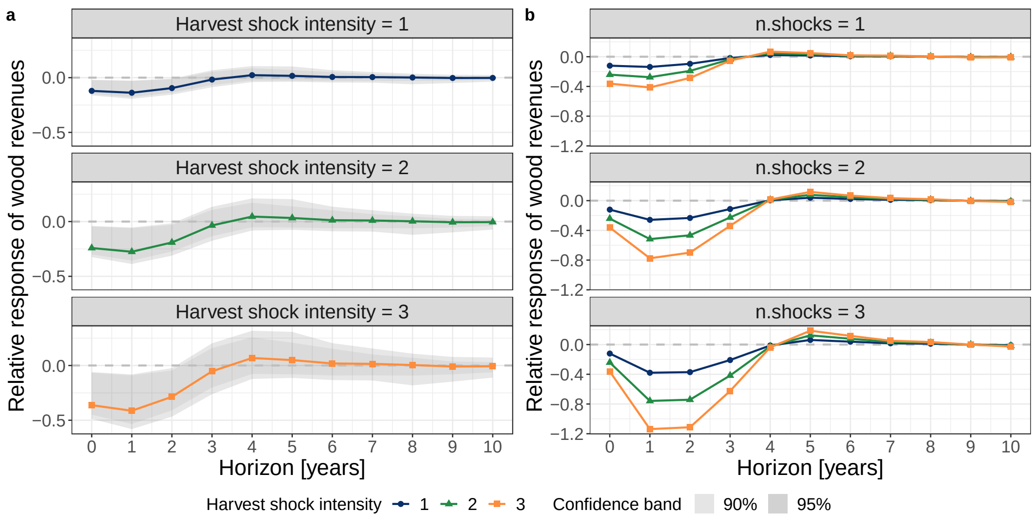

Figure 2: Impulse response of the relative wood revenues of spruce on supply shocks of harvest volume for different shock intensities (a) and multiple subsequent disturbances (b). Shock intensities denote the magnitude of the supply shock (harvest volume) in relation to the non-calamity year 2013. n.shocks denotes the number of subsequent years with supply shocks. The maximum shock observed in the data was about 3.54. Please note that the years > 5 are shown to reveal that the shocks subside to 0. The responses after 5 years should be interpreted as being 0. Confidence intervals were derived from $2,000$ bootstrap iterations.

were estimated even for a shock intensity of 2[5].

To summarize, the IRFs suggest remarkable reductions in spruce revenues for historically realistic shocks in the harvest volume, i.e. higher wood supply. The different shock intensities further illustrate that these reductions might considerably differ dependent on the severity of the disturbance event. We further found that the revenues recovered quite quickly and reached their previous level in the third year after the simulated disturbance.

[5]Please note that responses resulting in negative revenues ($responses < -1$) arise due to the linearity of VARs and are a model artifact, see Section 5. Such values would mean that the wood buyer is paid for taking the wood, as our study refers to gross revenues.

3.2.2 Beech

Based on the Granger Causality results, we focused on shocks in the share of damaged wood in the case of beech. The IRFs of the wood revenues on higher shares of damaged wood revealed a small but significant decrease in revenues after disturbances (Fig. 3 and Tab. A1). The revenues recovered within 4 years. Assuming an increase of 0.3 in the share of damaged wood, the reduction in revenues was about 0 in the year of the shock, and raised up to 9 % in the second year. Thus, in contrast to supply shocks for spruce, the onset of the decline in revenues after quality shocks of beech was more delayed. This might, for example, be related to longer storage times before sale. The decrease of only 9 % for an increase in the share of damaged wood of 0.3 seems to be comparably small. However, one should consider that the 0.3 shock refers to the average share of damaged wood sold by HessenForst in one year. In contrast, regarding a single stand, a disturbance event can lead to an increase of 100 percentage-points in the share of damaged wood with a corresponding decrease in revenues of up to 30 %.

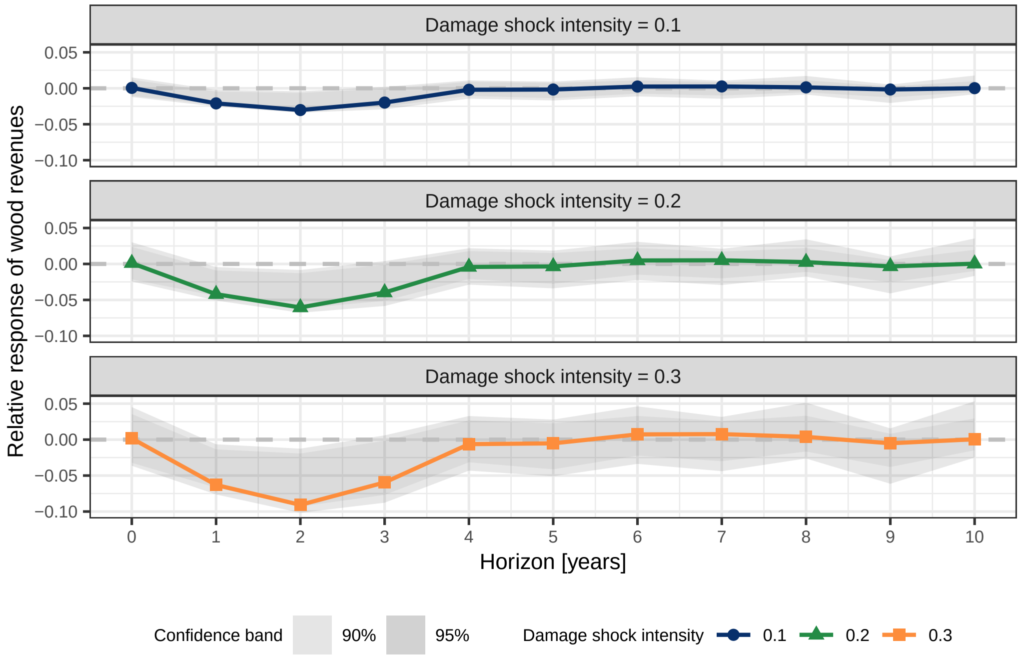

Figure 3: Impulse response of the relative wood revenues of beech on shocks in the share of damaged wood. Shock intensities denote the additional share of damaged wood. The maximum shock observed in the data was about 0.38. Please note that the years > 5 are shown to reveal that the shocks subside to 0. The responses after 5 years should be interpreted as being 0. Confidence intervals were derived from 2,000 bootstrap iterations.

4 Derivation of reduction factors for salvage revenues (*Q5*)

In this section, we illustrate for future bioeconomic models how our econometric results can be translated into simplified reduction factors for salvage revenues. These factors will be implemented in a wood valuation model for Central Germany provided as `R`-package `woodValuationDE`. This step required the incorporation of expert knowledge in order to add assumption on the increase of harvest costs and to critically interpret our econometric IRF results against the background of the underlying data. We expect our exemplifying suggestions to be useful for a wide range of bioeconomic studies, but recommend extensive sensitivity analyses, particularly for beech, due to some limitations in our study (see Section 5).

We calculated factors, by which wood revenues are reduced, for 3 different spatial extents of disturbances: small disturbances affecting only single stands, those of regional relevance (Hesse in our study), and transregional calamities. For small disturbances, we propose only the consideration of the quality effect since it is unlikely that such marginal additional salvage volumes will affect regional (Hessian) wood markets. In contrast, we suspect that regional disturbances additionally cause oversupply and thus a decline in market prices. Consequences of transregional calamities were implemented by adding the estimated dummy variable for calamity years.

We calculated these factors as the mean IRF of a 5 year horizon, which is a typical time period in forest management plans and yield tables. For the shock intensity of the harvest volume, we took the 0.95 quantile of the observed harvest volume, i.e. shock intensity 3.39 for spruce and 0.19 for beech. For the shock in damaged wood, we assumed an increase from 0 to 100 %, since it is most likely that a harvest measure is recorded as damaged or undamaged in the operational data, irrespective of the actual shares of damaged trees. Thus, the assumption that the entire volume of a salvage harvest is recorded as damaged does not overestimate the actual damages. The proposed factors (Tab. 3) can be interpreted as aggregations of market effect, quality effect, and the calamity dummy variable (for the full calculations see Supplement C).

Table 3: Suggested factors for the reduction in wood revenues and increase in harvest costs for salvage harvests.

Disturbance extent	Relative reduction in wood revenues	Relative increase in harvest costs
Spruce		
stand	10 %	15 %
region	34 %	15 %
transregional	54 %	25 %
Beech		
stand	15 %	15 %
region	30 %	15 %
transregional	30 %	25 %

For spruce, our models could not identify a considerable quality effect, however, at least a small effect seems plausible (see Section 5). An additional analysis (Supplement A.VI) generally confirmed the econometric results and suggested a quality-related decrease in revenues of 1 to 8 % in calamity years. We thus assumed an effect of quality losses of 10 % for 5 year horizons for conservative economic calculations at the stand level. Thus, we suggest, based on our empirical results, that disturbances in single-stands have a rather limited effect on spruce revenues while considerable market effects lead to losses of 54 % after transregional calamities.

For beech, no large calamities, which could have led to oversupply, were observed in our data. We therefore assumed that future supply peaks may indeed have a market effect. However, we expect this effect to be smaller than that calculated for spruce, since beech is not known to respond with sudden, synchronized mortality events (see Section 5). We thus assumed a market effect, which reduces revenues by 15 %. Therefore, we suggest that wood from salvage harvests of beech has a lower quality and suspect an additional market effect after future, larger disturbances. However, we strongly recommend sensitivity analyses.

The assumed increase in harvest costs for salvage harvests (Tab. 3) was determined based on expert knowledge as well as recent experience with contracts of HessenForst for highly mechanized harvest operations. We distinguished between effects of higher efforts for harvest operations in damaged stands and additional costs in situations where capacities are limited due to an increased demand, such as after transregional calamities.

5 Discussion

Our study demonstrated that SVARs have a high potential for estimating the economic consequences of forest disturbances. Previous studies on the effects of disturbances on wood markets analyzed effects of single, specific disturbance events (e.g. Prestemon & Holmes, 2000; Sun, 2016; Yin & Newman, 1999; Zhai & Kuusela, 2020). In contrast, the SVARs allowed us to study the potential feedback of revenues on a variety of hypothetical disturbance-induced shocks. We see a particular advantage in standardizing the shocks (cf. Lemoine, 2021), as this improves the applicability of the empirical results for future simulation modeling. In addition, time series methods proved useful in making operational data, which were not collected for research purposes, available for econometric analysis.

Q1: Decreasing revenues of spruce after disturbances were mainly related to an increase in wood supply. In contrast, the decreasing revenues of beech were mainly related to a reduced quality.

The importance of oversupply for spruce revenues confirms the findings of, e.g., Toth et al. (2020), who found a strong effect of increased salvage logging due to bark beetle calamities on Czech wood prices. Falling market prices for wood apparently do not prevent oversupply, if forest management cannot entirely compensate the salvage volumes by reducing planned harvest activities (see Bergen et al., 2013). This unavoidable salvage supply can be expected to be inelastic to changes in wood prices (e.g. Marsinko et al., 1996; Prestemon & Holmes, 2008), making it a key driver of price dynamics, as indicated by our results. Additionally, changes in wood demand, such as those hypothesized for sawmill by-products in Austria (Fuhrmann et al., 2021), may influence the wood market. These effects were out of the scope of our analysis, but can be assumed to be of minor importance for spruce since our supply model already reached a high explanatory power.

We could not identify a considerable decline of spruce revenues due to losses in wood quality after disturbances. However, the share of wood recorded as damaged increased in calamity years (Fig. 1). In fact, the detailed assortment data showed that the average quality of sawlogs was reduced. Nevertheless, the altered assortment composition seemed to be less important for the averaged revenues, since the share of the low-value pulpwood ranged between 20 and 28 % over all years (Supplement A.VII) and thus, at most, increased only slightly. In their survey, which focused solely on quality losses, Möllmann and Möhring (2017) found 15.2 % lower revenues for conifers after disturbances. On the one hand, it is conceivable that market and quality effects cannot be strictly separated based on expert knowledge. On the other hand, this indicates that there could at least be a small quality effect for spruce, which could not be identified by our VAR estimation due to, e.g., the time series covering only 16 years.

In contrast to spruce, we did not find a clear influence of the harvest volume on beech revenues. This may be partially explained by the observed harvest volumes of beech (Fig. 1a), which were largely constant. Thus, a potential reaction of beech market prices to oversupply is well possible, if future disturbances lead to higher supplies than observed in our study. The period of drought and heat (2018-2020) with synchronized calamities across Central Europe (see Senf & Seidl, 2021b), might have increased mortality rates of beech (Obladen et al., 2021). However, salvage harvests of beech are most likely lagged because timely sanitation fellings in spruce forests limit the harvest capacity, and mortality due to drought occurs less suddenly than storm events.

The less conclusive VAR estimations for beech compared to spruce suggest that further variables influence beech revenues. For example, increasing hazard probabilities with age (Staupendahl, 2011) may lead to higher shares of larger beech trees in salvage harvests. Since larger trees usually contain higher shares of valuable sawlogs (e.g. Offer & Staupendahl, 2018), the decreased wood quality after disturbances might be partially covered by a generally higher quality in the damaged subgroup. However, based on our data sets, we were not able to explicitly capture this effect, e.g., by VARs considering diameters or the shares of sawlogs. Future studies with data which directly link disturbances to assortment compositions may provide more detailed insights. Furthermore, the consideration of other exogenous effects in related markets (cf. Zhai & Kuusela, 2020) may improve the models for beech. Interesting aspects in our context could be financial crises (Schick, 2019) and oil-price induced changes in fuelwood demand (Härtl & Knoke, 2014).

None of the VAR models showed evidence for instability. The residuals did not contain autocorrelation (Supplements A: Fig. 1, B: Fig. 3), and adding additional time series (Supplements A.V, B.V) did not alter the observed trends, which emphasizes the consistent estimation of the VAR. For example, Adenomon et al. (2015) found that for time series data with a limited sample size, even high correlation (> 0.9) among the variables did not require any correction procedure. However, it is noteworthy that the limited sample size in our analysis does not allow for a straightforward increase of model dimensionality. Against this background, panel VARs (PVARs) would be a promising model class for future analyses. For instance, under common homogeneity assumptions and exploitation of the region structure within data, pooled regressions would significantly increase the degrees of freedom (see e.g. Baltagi et al., 2000). Since this goes beyond the scope of this paper, we leave this interesting topic for future research.

Q2: Transregional calamities additionally reduced spruce revenues by about 20 %.

Years with transregional calamities generally differed from those without calamities. Consequently, model selection chose the integration of a dummy variable for calamity years. This suggests that wood markets of neighboring regions influence each other, as shown by Zhou and Buongiorno (2006) for the U.S., and that declining prices at regional markets are additionally driven by the salvage harvests in neighboring regions. The dummy variable might also capture effects that arise at high supply rates but cannot be fully incorporated in the linear VARs (Equation 1). Such effects can be limited transport or storage capacities of sawmills that suddenly limit a further increase in the short-term demand for wood. The dummy variable's influence on beech revenues was small and positive and is probably a model artifact related to the less conclusive VAR estimations.

Q3: The reduction in revenues was highly sensitive to the assumed disturbance severity. The negative effect subsided within 3-4 years.

Our results fit well with factors applied in earlier studies, but relate the decline in revenues directly to characteristics of the disturbance event. For instance, increasing the harvest volume of spruce by a factor of 2 reduced revenues by about 28 % (Fig. 2), which is close to the 30 % in Staupendahl and Möhring (2011). Assuming the same regional intensity but a transregional extent (by considering the additional calamity dummy variable, Tab. 1), we received a reduction of about 48 % (cf. 50 % in Dieter, 2001, but for net revenues). This shows that explicitly linking the decline in wood revenues to the assumed disturbance severity and its spatial extent is important for interpreting its simulated economic impact. As compared to earlier estimates based on expert-knowledge, such as Dieter (2001) or Staupendahl and Möhring (2011), our approach allows for the characterization of the assumed disturbance events and the consideration of the development of revenues in the years after the event. In line with, e.g, Yin and Newman (1999), the short-run negative loss in revenues subsided quite quickly, limiting the adverse economic consequences. We focused on the short-term effects of disturbances, however, the short recovery period in the IRFs may indicate that there was no long-term effect on wood prices, with reduced inventories leading to lower supply and increased market prices (cf. e.g. Prestemon & Holmes, 2000, 2008). This could change in the near future, due to subsequent, transregional calamities in recent years with considerable damage, especially in spruce forests (cf. Möhring et al., 2021).

In Möllmann and Möhring (2017), the quality effect was more important for deciduous species (−21.3 %) than for conifers (−15.2 %). While we could not confirm the quality effect for spruce, the estimated effect for beech was even higher. When comparing damaged and undamaged stands, i.e. a shock of 100 % in the share of damaged wood, our IRFs suggested a decrease of up to 30 % in beech revenues. Nevertheless, our results may actually underestimate the quality effect for beech due to a possible bias we could not capture in our estimation. Practical experience, particularly in recent years, has emphasized that beech trees which have strongly deteriorated in quality are not economical to harvest, while sanitation felling is not necessary. Hence, parts of the severely damaged beech trees were most likely not considered in our harvest and sales data and, in contrast, are preserved as habitat trees.

Q4: Declines in revenues after multiple disturbances in subsequent years far exceed declines after single events.

We even found a complete loss of revenues in subsequent large disturbances (Fig. 2b). However, our study refers to gross revenues. The estimated negative revenues (IRF < -1) are presumably a model artifact due to the linearity assumption in VARs (Equation 1). In contrast to this assumption, a non-linear relationship between wood supply and market prices could be hypothesized (cf. e.g. Prestemon & Holmes, 2008). For example, an increasing attractiveness of export markets, such as China, may buffer parts of the oversupply and decline in local market prices (Toth et al., 2020), underlining the fact that the VAR estimates should be extrapolated with care.

Q5: Our results shed new light on the quantitative understanding of the consequences of disturbances for wood revenues. Their implications are informative for future bioeconomic forest modeling of impacts of and adaptation to climate change as well as for practical forest management decisions.

Our results recommend distinguishing the consequences of disturbances for wood revenues by tree species, spatial extent, and time since the event.

Thus, simulation studies applying simplified assumptions, such as constant reduction factors for salvage revenues, might only partially capture the underlying mechanisms. Future bioeconomic simulations should account for losses in beech revenues due to lower quality, while focusing on the market effect for spruce. Studies aiming to differentiate between regularly occurring minor disturbances and synchronized transregional calamities should also consider the disturbances' spatial extents in the economic valuation. For example, disturbances in single stands most likely cause limited quality losses rather than affecting market prices.

In order to simplify the application of our econometric results for Central Germany, we proposed reduction factors for salvage revenues. However, in particular for beech, our VAR estimations were inconclusive, which might be related to the discussed length of our time series and the historic development of beech harvest volumes. Consequently, we had to apply some expert-based assumptions during the derivation of these factors. We therefore recommend a critical application with intensive sensitivity analyses. We further emphasize that the derived reductions in revenues refer to the actual volume sold. After disturbances, the economic situation of a forest enterprise can be further impaired by larger proportions of harvest residuals or damaged but unsalvaged volumes (e.g. Möhring et al., 2021). The amount of unsalvaged volumes would therefore need to be estimated separately if required in future applications.

The length of the time series was a technical limitation for the applied statistics and the data referred to only one forest enterprise. The operational data set, with a large number of harvest and sales records behind each year, nevertheless allowed us to derive informative and reliable results for spruce and important indications for mechanisms in the case of beech. The spruce harvest volumes of HessenForst had a high explanatory power at the regional wood market. The Hessian softwood supply chains are typical for German spruce supply chains with a limited number of large timber industry companies supplying their products to national and European, but also to the world market (for a map of the German sawmill industry see Döring et al., 2017). The supply chains for beech can be expected to be more specialized since Hesse has the highest shares of beech in Germany (Thünen-Institut, 2015). The regional aggregation of hardwood-based industries (cf. e.g. Döring et al., 2017) indicates an above-average demand. We expect the qualitative results on market and quality effect for spruce, but with a few limitations also those for beech, to be well transferable to other Central European regions. Nevertheless, one should consider that the VARs and IRFs were derived based on the historic developments and might not cover future changes in wood demand, e.g., as feedstock for an expanding bioeconomy (e.g. Hennig et al., 2016), or possible effects of increased or altered disturbance dynamics (e.g. Seidl et al., 2017; Senf & Seidl, 2021a).

Our results are relevant for forest management in that we identified oversupply as a key reason for declining spruce revenues after disturbances on a quantitative basis. This implies that disturbances in spruce are of minor importance for a forest enterprise's revenues as long as spatially synchronized, large-volume salvage harvest can be avoided. Our results underline the importance of integrating spruce in less vulnerable mixed stands (e.g. Brandl et al., 2020; Griess et al., 2012) with lower shares in the species portfolio. This would reduce the total volume of a single species at risk during disturbances. Under such strategies, spruce might still be an economically reasonable tree species – despite its comparably high mortality probabilities (cf. e.g. Fuchs et al., 2022; Paul et al., 2019). Our results further suggest that the common practice of storing spruce after disturbances (Zimmermann et al., 2018) can indeed be promising in mitigating high losses in revenues. On the one hand, the immediate oversupply can be mitigated, which may restrain the decline in revenue. On the other hand, a value-preserving storage may help to avoid selling wood in a poor market situation one or two years (Fig. 2a) after disturbances.

6 Conclusion and outlook

From our study, we conclude that SVARs and IRFs are promising tools for exploring the economic consequences of disturbance events for forest enterprises. Our application of these econometric methods to Central European harvest and sales data highlight the importance of distinguishing between two reasons for disturbance-induced losses in revenues: 1) The quality reduction due to biophysical damages and 2) the market price reduction due to oversupply. Most importantly, we found that these effects are species-sensitive, with declining spruce revenues being mainly related to oversupply and those of beech mainly to quality losses. This finding is likely to apply to other species, but also to other countries due to differences in contracting practices, wood assortments, and disturbance patterns.

The quantitative results on market and quality effects are of high relevance for future bioeconomic models. We suggest factors by which revenues are assumed to be reduced in the case of disturbance events. These species-specific factors allow, for example, for an improved consideration of severity and spatial extent of (stochastic) disturbance events when implementing their economic consequences in Monte-Carlo simulations to support species selection (cf. Fuchs et al., 2022).

Future econometric studies could refine our approach for the consideration of spatial extent and synchronization of disturbance-induced revenue losses. A promising alternative to our dummy variable for disturbances of transregional extent are space-time models (cf. Zhou & Buongiorno, 2006), which explicitly estimate the interactions between neighboring submarkets.

For bioeconomic modeling, such information would allow for the consideration of the spatial dependency of losses in revenues after disturbances. This would be of high appeal, for example, for exploring economic adaptation strategies to spatially correlated extreme weather events in landscape-level simulations.

However, our study also clearly underlines the challenges and limitations of operational data sets for econometric studies. Future studies could overcome some limitations of our analyses, particularly the short time series, by using data from private forest enterprises. They often have access to longer time series, which would allow for the consideration of more covariables, for example, related to wood demand. However, the data would represent a smaller proportion of a state's harvests and sales and might be less representative for the trends on regional wood markets and other forest enterprises. It could also be of interest to distinguish models between disturbance agents, such as bark beetles and storms (cf. Möllmann & Möhring, 2017). Regarding beech, the current drought period in Germany may provide additional data of more severe damages in beech forests (cf. Obladen et al., 2021; Schuldt et al., 2020), which could be used to test the indications identified in our study.

We provide an example for applications of the often available but challenging operational data sets in time series analyses. Despite the further developments needed, we believe that such retrospective analyses may offer important information for future forest management decisions under climate change.

Online supplement

The following supplementary material is available online: Supplement A, B: the detailed statistical analyses and model summaries for spruce (A) and beech (B). Supplement C: calculation of the factors in Tab. 3. Supplement D: the time series data.

Data availability

The original data sets underlying this article cannot be shared publicly since they contain detailed operational data. The derived time series are available as Supplement D. The harvest statistics of Germany are publicly available at Genesis Online. The wood valuation model will be available as `R`-package woodValuationDE at CRAN.

CRediT authorship contribution statement

JF: Conceptualization, Methodology, Formal analysis, Data Curation, Writing – Original Draft, Visualization; HvB: Conceptualization, Data Curation, Writing – Review & Editing; AL: Methodology, Writing – Review & Editing; CP: Conceptualization, Writing – Review & Editing; KH: Conceptualization, Methodology, Formal analysis, Writing – Review & Editing

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Table A1: Impulse response of the relative averaged wood revenues on shocks of harvest volume (spruce) or share of damaged wood (beech) for the first 5 years. Shock intensities denote the magnitude of the harvest volume supply shock in relation to the time series mean or the additional share of damaged wood, respectively.

Shock intensity	Horizon [years]					
	0	1	2	3	4	5
Spruce: impulse of harvest volume						
1	-0.121	-0.138	-0.095	-0.018	0.023	0.016
2	-0.241	-0.276	-0.191	-0.035	0.046	0.033
3	-0.362	-0.413	-0.286	-0.053	0.068	0.049
Beech: impulse of share of damaged wood						
0.1	0.001	-0.021	-0.030	-0.020	-0.002	-0.002
0.2	0.001	-0.042	-0.061	-0.040	-0.004	-0.003
0.3	0.002	-0.063	-0.091	-0.060	-0.006	-0.005

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Online supplement

Supplement A: Detailed analyses spruce

Supplementary material to *Quantifying the consequences of disturbances on wood revenues with Impulse Response Functions*

Contents

I. Pre-analyses of the data sets

```
library(tidyverse)
library(tseries)
library(vars)
library(kableExtra)
library(corrplot)
library(ggpubr)
```

I.1. Lag order selection harvest and sale volumes

We tested whether there is evidence for any time lag between the annual volumes of harvests and sales data. For this, we conducted a lag order selection testing a maximum lag order lag.max = 2.

```
lago.vol <- VARselect(dat.spruce.rel[, c("harvest.vol",
                                          "sale.vol")],
                      type = "const",
                      lag.max = 2,
                      exo = dat.spruce.rel[, "calamity"])
```

Table 1: Lag order selection (lag.order in years) of harvest volume and sale volume based on 4 selection criteria.

criterion	lag.order
AIC	2
HQ	2
SC	1
FPE	2

All criteria suggested a lag order > 0 (Tab. 1), which confirmed that the series had inter-annual relationships. Therefore, we applied methods of time series analysis for the subsequent analyses.

I.2. Correlations

Table 2: Correlations between the variables.

	revenues	harvest.vol	share.wood.damaged
revenues	1.00	-0.76	-0.70
harvest.vol	-0.76	1.00	0.83
share.wood.damaged	-0.70	0.83	1.00

II. Market effect

II.1. Model selection

We selected the VAR model based on two lag order selections with lag orders of up to only 3 years, as our time series had a length of only 16 years. Higher lag orders could have led close to a saturated model. Restricting the lag order also reduced potential problems with multicollinearity. We tested models with and without the dummy variable for years with transregional calamities.

```
# without dummy
lago.harv.rev <- VARselect(
  dat.spruce.rel[, c("harvest.vol",
                     "revenues")],
  type = "const",
  lag.max = 3)

# with dummy
lago.harv.rev.dummy <- VARselect(
  dat.spruce.rel[, c("harvest.vol",
                     "revenues")],
  type = "const",
  lag.max = 3,
  exo = dat.spruce.rel[, "calamity"])
```

Table 3: Lag order selection (lag order in years) of harvest volume and average wood revenues based on 4 selection criteria. Tested for 3 years at maximum.

model	AIC	FPE	HQ	SC
lag order 2 + dummy	-8.1	0.000347	-8.22	-7.60
lag order 2	-7.8	0.000447	-7.88	-7.36
lag order 3 + dummy	-7.7	0.000650	-7.89	-7.05
lag order 3	-7.6	0.000647	-7.72	-6.99
lag order 1 + dummy	-5.8	0.003136	-5.88	-5.46
lag order 1	-5.0	0.006908	-5.05	-4.73

All criteria suggested a lag order of 2 years. The models including dummy variables for years with transregional calamities performed better in terms of AIC (Tab. 3).

II.2. VAR

II.2.1. VAR estimation

We fitted a VAR according to the model selection to determine the effect of the harvest volume (market effect) on wood revenues.

```
var.harv.rev <- vars::VAR(
  as.ts(dat.spruce.rel[, c("harvest.vol",
                           "revenues")],
        start = 2005),
  p = 2,
  type = "const",
  ic = "AIC",
  exogen = dat.spruce.rel[, "calamity"])

summary(var.harv.rev)
```

```
##
## VAR Estimation Results:
## =========================
## Endogenous variables: harvest.vol, revenues
## Deterministic variables: const
## Sample size: 14
## Log Likelihood: 28.728
## Roots of the characteristic polynomial:
## 0.7173 0.7173 0.598 0.598
## Call:
## vars::VAR(y = as.ts(dat.spruce.rel[, c("harvest.vol", "revenues")],
##     start = 2005), p = 2, type = "const", exogen = dat.spruce.rel[,
##     "calamity"], ic = "AIC")
##
##
## Estimation results for equation harvest.vol:
## ============================================
## harvest.vol = harvest.vol.l1 + revenues.l1 + harvest.vol.l2 + revenues.l2 + const + calamity
##
##                 Estimate Std. Error t value Pr(>|t|)
## harvest.vol.l1  0.008583   0.212554   0.040   0.9688
## revenues.l1    -3.408894   3.064179  -1.112   0.2982
## harvest.vol.l2 -0.354536   0.240853  -1.472   0.1792
## revenues.l2    -0.058336   1.768443  -0.033   0.9745
## const           5.126792   2.590041   1.979   0.0831 .
## calamity        2.212032   0.611405   3.618   0.0068 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 0.5855 on 8 degrees of freedom
## Multiple R-Squared: 0.8918,  Adjusted R-squared: 0.8242
## F-statistic: 13.19 on 5 and 8 DF,  p-value: 0.001079
##
##
## Estimation results for equation revenues:
## =========================================
## revenues = harvest.vol.l1 + revenues.l1 + harvest.vol.l2 + revenues.l2 + const + calamity
```

```
##
##                Estimate Std. Error t value Pr(>|t|)
## harvest.vol.l1 -0.05385    0.02693  -1.999   0.0806 .
## revenues.l1     0.69522    0.38824   1.791   0.1111
## harvest.vol.l2 -0.04041    0.03052  -1.324   0.2220
## revenues.l2    -0.52564    0.22407  -2.346   0.0470 *
## const           0.90208    0.32817   2.749   0.0251 *
## calamity       -0.20189    0.07747  -2.606   0.0313 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 0.07418 on 8 degrees of freedom
## Multiple R-Squared: 0.9287,  Adjusted R-squared: 0.8842
## F-statistic: 20.85 on 5 and 8 DF,  p-value: 0.000213
##
##
##
## Covariance matrix of residuals:
##             harvest.vol  revenues
## harvest.vol     0.34280 -0.041391
## revenues       -0.04139  0.005503
##
## Correlation matrix of residuals:
##             harvest.vol revenues
## harvest.vol       1.000   -0.953
## revenues         -0.953    1.000
```

II.2.2. Residual analysis

```
par(mfrow = c(2, 1))
pacf(resid(var.harv.rev)[,"revenues"],
     main = "PACF of the Residuals")
acf(resid(var.harv.rev)[,"revenues"],
    main = "ACF of the Residuals")
```

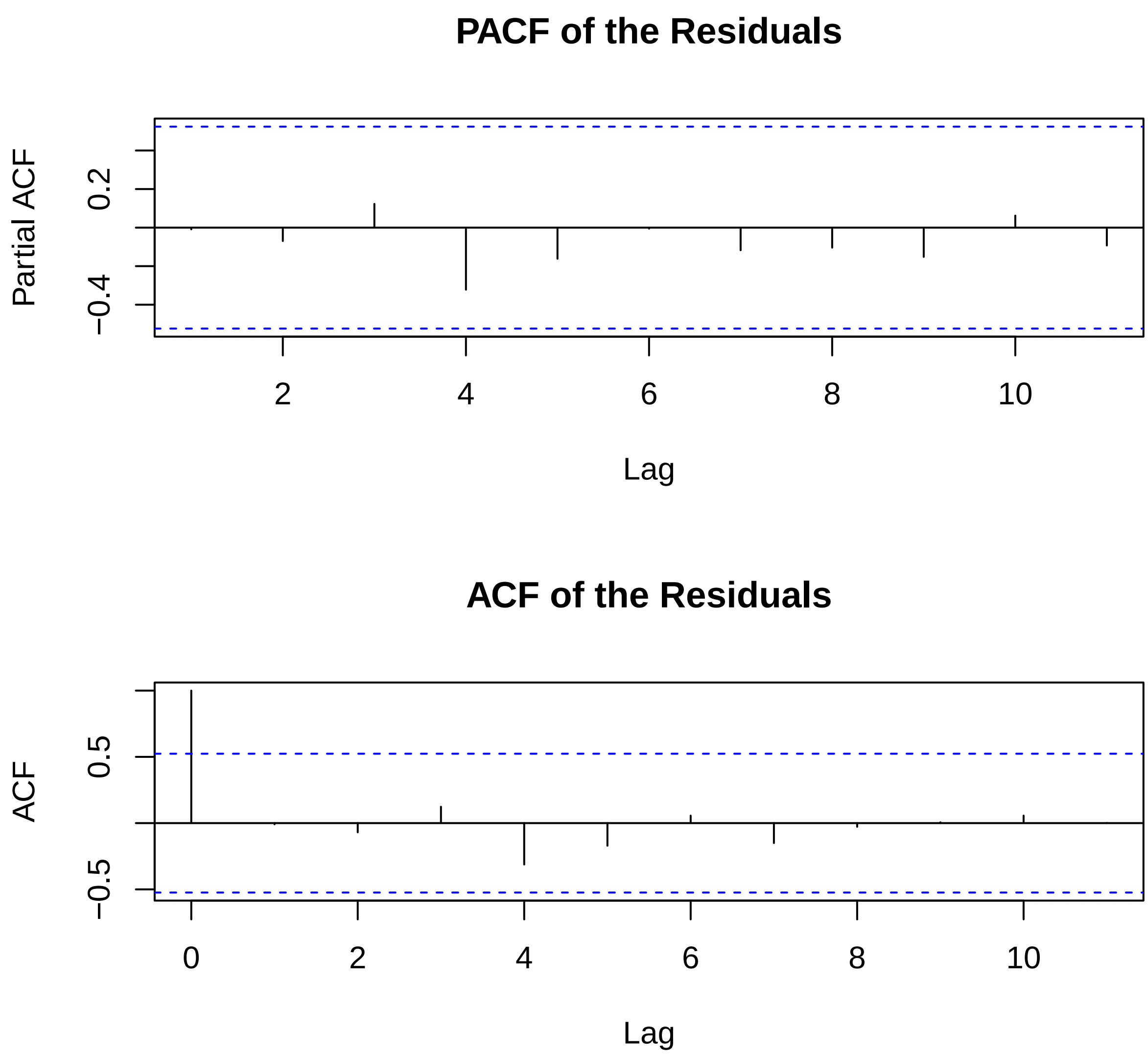

Figure 1: The autocorrelation function and the partial autocorrelation function reveal no remarkable autocorrelation of the model residuals. It can be followed that there is no evidence against our assumption of consistently estimated residuals.

II.3. SVAR and IRF

II.3.1. Shocks of varying intensity

Based on the estimated reduced-form VAR, we calculated SVARs and IRFs for shocks of varying intensity.

```
shock.intensities <- 1:3

dat.harv.rev.plot <- tibble()

var.harv.rev.irf.orig <- vars::irf(
  var.harv.rev,
  n.ahead = 10,
  ci = 0.95,
  runs = 2000,
  ortho = TRUE)

for (i in shock.intensities) {

  var.harv.rev.irf <- var.harv.rev.irf.orig

  # rescaling the IRF to modify the shock intensity
  # (identical to modifying the B matrix as described in the manuscript)
  var.harv.rev.irf$irf$harvest.vol <-
    (var.harv.rev.irf.orig$irf$harvest.vol /
       var.harv.rev.irf.orig$irf$harvest.vol[1, 1]) *
    i

  dat.harv.rev.plot <- dat.harv.rev.plot %>%
    bind_rows(
      c(shock.intensity = i,
        corr.factor = 1 /
          var.harv.rev.irf.orig$irf$harvest.vol[1, 1] *
          i,
        var.harv.rev.irf$irf$harvest.vol[, 2])
    )

}
```

For the results, see also Figure 2a in the main text.

II.3.2. Multiple shocks in subsequent years

Additionally, we simulated the IRFs for multiple shocks in subsequent years.

```
dat.harv.rev.plot.gath <-
  dat.harv.rev.plot %>%
  gather("horizon",
         "response.revenues",
         -shock.intensity,
         -corr.factor) %>%
  mutate(horizon = as.numeric(horizon))

dat.harv.rev.mult.shocks <-
  dat.harv.rev.plot.gath %>%
  group_by(shock.intensity) %>%
  arrange(shock.intensity,
```

Table 4: Impulse response of average revenues on shocks in the harvest volume. The shock intensity denotes the magnitude of the additional harvested volume in relation to the harvest volume in 2013. The maximum observed shock in the time series was about 3.54.

horizon	shock.intensity = 1	shock.intensity = 2	shock.intensity = 3
0	-0.121	-0.241	-0.362
1	-0.138	-0.276	-0.413
2	-0.095	-0.191	-0.286
3	-0.018	-0.035	-0.053
4	0.023	0.046	0.068
5	0.016	0.033	0.049
6	0.006	0.012	0.019
7	0.005	0.010	0.015
8	0.001	0.003	0.004
9	-0.003	-0.006	-0.009
10	-0.002	-0.005	-0.007

```
          horizon) %>%
  mutate(
    `n.shocks = 1` = response.revenues,
    # two (additive) shocks of the same intensity
    `n.shocks = 2` = response.revenues +
      lag(response.revenues,
          default = 0),
    # three (additive) shocks of the same intensity
    `n.shocks = 3` = `n.shocks = 2` +
      lag(response.revenues,
          default = 0)
  )
```

For the results, see also Figure 2b in the main text.

Table 5: Impulse response of average revenues on multiple shocks in the harvest volume. The shock intensity denotes the magnitude of the additional harvested volume in relation to the harvest volume in 2013. The maximum observed shock in the time series was about 3.54. n.shocks denotes the number of subsequent calamity years. Multiple shocks are assumed to be additive due to the linear formulation of VAR models.

shock.intensity	horizon	n.shocks = 1	n.shocks = 2	n.shocks = 3
1	0	-0.121	-0.121	-0.121
1	1	-0.138	-0.259	-0.379
1	2	-0.095	-0.233	-0.371
1	3	-0.018	-0.113	-0.208
1	4	0.023	0.005	-0.012
1	5	0.016	0.039	0.062
1	6	0.006	0.023	0.039
1	7	0.005	0.011	0.017
1	8	0.001	0.006	0.011
1	9	-0.003	-0.002	0.000
1	10	-0.002	-0.005	-0.009
2	0	-0.241	-0.241	-0.241
2	1	-0.276	-0.517	-0.759
2	2	-0.191	-0.466	-0.742
2	3	-0.035	-0.226	-0.417
2	4	0.046	0.010	-0.025
2	5	0.033	0.078	0.124
2	6	0.012	0.045	0.078
2	7	0.010	0.022	0.035
2	8	0.003	0.013	0.023
2	9	-0.006	-0.003	-0.001
2	10	-0.005	-0.011	-0.017
3	0	-0.362	-0.362	-0.362
3	1	-0.413	-0.776	-1.138
3	2	-0.286	-0.699	-1.113
3	3	-0.053	-0.339	-0.625
3	4	0.068	0.016	-0.037
3	5	0.049	0.118	0.186
3	6	0.019	0.068	0.117
3	7	0.015	0.033	0.052
3	8	0.004	0.019	0.034
3	9	-0.009	-0.005	-0.001
3	10	-0.007	-0.016	-0.026

III. Quality effect

III.1. Model selection

In line with the VAR analysis on the harvest volume, we selected the VAR model for the share of damaged wood based on two lag order selections with lag orders up to 3 years, and tested models with and without a dummy variable for large-scale calamities.

```
# without dummy
lago.dam.rev <- VARselect(
  dat.spruce.rel[, c("share.wood.damaged",
                     "revenues")],
  type = "const",
  lag.max = 3)

# with dummy
lago.dam.rev.dummy <- VARselect(
  dat.spruce.rel[, c("share.wood.damaged",
                     "revenues")],
  type = "const",
  lag.max = 3,
  exo = dat.spruce.rel[, "calamity"])
```

Table 6: Lag order selection (lag order in years) of the share of damaged wood and average wood revenues based on 4 selection criteria. Tested for 3 years at maximum.

model	AIC	FPE	HQ	SC
lag order = 2	-8.3	0.000272	-8.38	-7.86
lag order = 2 +dummy	-8.2	0.000305	-8.35	-7.72
lag order = 3 +dummy	-7.9	0.000534	-8.09	-7.25
lag order = 3	-7.9	0.000481	-8.02	-7.28
lag order = 1 +dummy	-7.5	0.000589	-7.55	-7.13
lag order = 1	-6.8	0.001189	-6.81	-6.49

All criteria suggested a time lag of 2 years without a calamity dummy (Tab. 6). However, the AICs of the models with and without a dummy were very similar. We therefore decided to use the model with a dummy variable anyway to enhance the comparability with the model for the market effect.

III.2. VAR

III.2.1. VAR estimation

We fitted a VAR according to the model selection to determine the effect of the share of damaged wood (quality effect) on wood revenues.

```
var.dam.rev <- vars::VAR(
  as.ts(dat.spruce.rel[, c("share.wood.damaged",
                           "revenues")],
        start = 2005),
  p = 2,
  type = "const",
  ic = "AIC",
  exogen = dat.spruce.rel[, "calamity"]
)

summary(var.dam.rev)
```

```
##
## VAR Estimation Results:
## =========================
## Endogenous variables: share.wood.damaged, revenues
## Deterministic variables: const
## Sample size: 14
## Log Likelihood: 28.215
## Roots of the characteristic polynomial:
## 0.8244 0.8244 0.7301 0.7301
## Call:
## vars::VAR(y = as.ts(dat.spruce.rel[, c("share.wood.damaged",
##     "revenues")], start = 2005), p = 2, type = "const", exogen = dat.spruce.rel[,
##     "calamity"], ic = "AIC")
##
##
## Estimation results for equation share.wood.damaged:
## ====================================================
## share.wood.damaged = share.wood.damaged.l1 + revenues.l1 + share.wood.damaged.l2 + revenues.l2 + cons
##
##                       Estimate Std. Error t value Pr(>|t|)
## share.wood.damaged.l1 -0.03640    0.33880  -0.107   0.9171
## revenues.l1           -1.90130    1.02670  -1.852   0.1012
## share.wood.damaged.l2 -0.53834    0.31146  -1.728   0.1222
## revenues.l2           -0.31173    0.65757  -0.474   0.6481
## const                  2.81881    1.01015   2.790   0.0235 *
## calamity              -0.00773    0.23388  -0.033   0.9744
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 0.2248 on 8 degrees of freedom
## Multiple R-Squared: 0.7201,  Adjusted R-squared: 0.5451
## F-statistic: 4.116 on 5 and 8 DF,  p-value: 0.03793
##
##
## Estimation results for equation revenues:
## =========================================
```

```
## revenues = share.wood.damaged.l1 + revenues.l1 + share.wood.damaged.l2 + revenues.l2 + const + calami
##
##                        Estimate Std. Error t value Pr(>|t|)
## share.wood.damaged.l1 -0.12723    0.13373  -0.951   0.3693
## revenues.l1            1.18437    0.40527   2.922   0.0192 *
## share.wood.damaged.l2  0.03923    0.12294   0.319   0.7578
## revenues.l2           -0.65021    0.25957  -2.505   0.0367 *
## const                  0.45949    0.39874   1.152   0.2824
## calamity              -0.13418    0.09232  -1.453   0.1842
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 0.08874 on 8 degrees of freedom
## Multiple R-Squared: 0.898,   Adjusted R-squared: 0.8343
## F-statistic: 14.09 on 5 and 8 DF,  p-value: 0.0008589
##
##
##
## Covariance matrix of residuals:
##                    share.wood.damaged  revenues
## share.wood.damaged            0.05054 -0.014546
## revenues                     -0.01455  0.007876
##
## Correlation matrix of residuals:
##                    share.wood.damaged revenues
## share.wood.damaged             1.0000  -0.7291
## revenues                      -0.7291   1.0000
```

III.2.2. Residual analysis

```
par(mfrow = c(2, 1))
pacf(resid(var.dam.rev)[,"revenues"],
     main = "PACF of the Residuals")
acf(resid(var.dam.rev)[,"revenues"],
    main = "ACF of the Residuals")
```

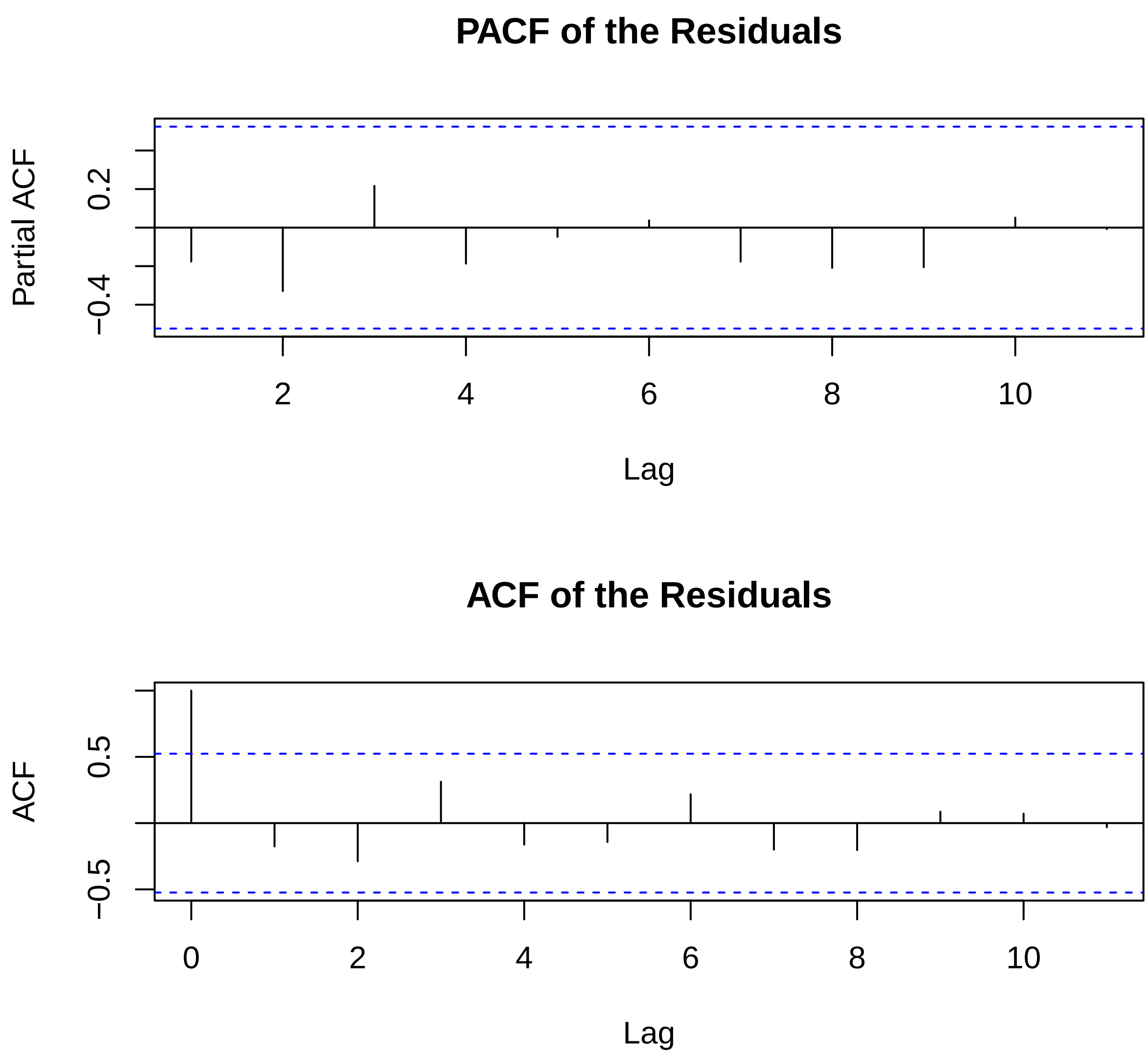

Figure 2: The autocorrelation function and the partial autocorrelation function reveal no remarkable autocorrelation of the model residuals. It can be followed that there is no evidence against our assumption of consistently estimated residuals.

III.3. SVAR and IRF

Based on the estimated reduced-form VAR, we calculated SVARs and IRFs for shocks of varying intensity.

```r
shock.intensities <- seq(0.1, 0.7, 0.2)

dat.dam.rev.plot <- tibble()

var.dam.rev.irf.orig <- vars::irf(
  var.dam.rev,
  n.ahead = 10,
  ci = 0.95,
  runs = 2000,
  ortho = TRUE)

for (i in shock.intensities) {

  var.dam.rev.irf <- var.dam.rev.irf.orig

  # rescaling the IRF to modify the shock intensity
  # (identical to modifying the B matrix as described in the manuscript)
  var.dam.rev.irf$irf$share.wood.damaged <-
    (var.dam.rev.irf.orig$irf$share.wood.damaged /
       var.dam.rev.irf.orig$irf$share.wood.damaged[1, 1]) * i

  dat.dam.rev.plot <- dat.dam.rev.plot %>%
    bind_rows(
      c(shock.intensity = i,
        corr.factor = 1 /
          var.dam.rev.irf.orig$irf$share.wood.damaged[1, 1] * i,
        var.dam.rev.irf$irf$share.wood.damaged[, 2])
    )

}
```

Table 7: Impulse response of average revenues on shocks in the share of damaged wood. The shock intensity denotes the magnitude of the additional share of damaged wood. The maximum observed, additional share of damaged wood to the non-calamity situation (2013) was about 0.76.

horizon	shock.intensity = 0.1	shock.intensity = 0.3	shock.intensity = 0.5	shock.intensity = 0.7
0	-0.029	-0.086	-0.144	-0.201
1	-0.047	-0.140	-0.234	-0.328
2	-0.039	-0.118	-0.197	-0.275
3	-0.019	-0.058	-0.097	-0.136
4	-0.004	-0.011	-0.018	-0.025
5	0.008	0.023	0.039	0.054
6	0.015	0.045	0.075	0.105
7	0.015	0.046	0.076	0.107
8	0.010	0.029	0.049	0.068
9	0.003	0.010	0.016	0.023
10	-0.002	-0.005	-0.008	-0.012

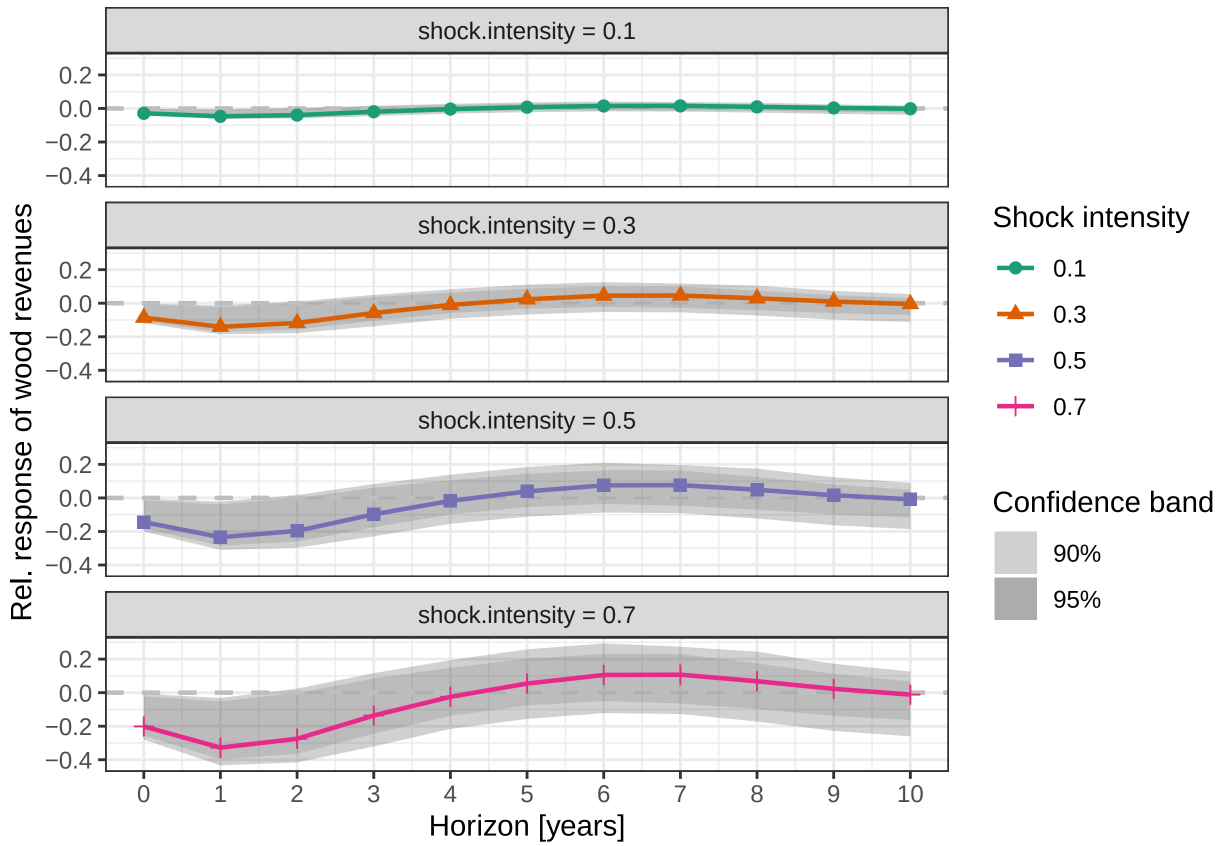

Figure 3: Impulse response of average revenues on shocks in the share of damaged wood. The shock intensity denotes the magnitude of the additional share of damaged wood. The maximum observed, additional share of damaged wood to the non-calamity situation (2013) was about 0.76.

IV. Granger causality

Linear hypothesis test, whether the harvest volume or the share of damaged wood Granger-causes revenues.

```
causality(var.harv.rev, cause = "harvest.vol")$Granger
```

```
##
##  Granger causality H0: harvest.vol do not Granger-cause revenues
##
## data:  VAR object var.harv.rev
## F-Test = 2.4246, df1 = 2, df2 = 16, p-value = 0.1203
```

```
causality(var.dam.rev, cause = "share.wood.damaged")$Granger
```

```
##
##  Granger causality H0: share.wood.damaged do not Granger-cause revenues
##
## data:  VAR object var.dam.rev
## F-Test = 0.48933, df1 = 2, df2 = 16, p-value = 0.6219
```

V. Combined market and quality effect

We also tested a VAR combining the effects of the harvest volume and share of damaged wood on revenues in one model.

V.1. Model selection

Due to the limited length of the time series, we tested a maximum lag order of 2 when considering 3 time series in one model.

```
lago.harv.dam.rev <- VARselect(dat.spruce.rel[, c("harvest.vol",
                                                  "share.wood.damaged",
                                                  "revenues")],
                               type = "const",
                               lag.max = 2,
                               exo = dat.spruce.rel[, "calamity"])
```

Table 8: Lag order selection (lag order in years) of harvest volume, share of damaged wood, and average wood revenues based on 4 selection criteria. Tested for 2 years at maximum.

model	AIC	FPE	HQ	SC
lag order 2 + dummy	-12.0	1.0e-05	-12.13	-10.93
lag order 1 + dummy	-9.3	9.9e-05	-9.38	-8.64

All criteria suggested a time lag of 2 years (Tab. 8).

V.2. VAR

V.2.1 VAR estimation

```r
var.harv.dam.rev <- vars::VAR(
  as.ts(dat.spruce.rel[, c("harvest.vol",
                           "share.wood.damaged",
                           "revenues")],
        start = 2005),
  p = 2,
  type = "const",
  ic = "AIC",
  exogen = dat.spruce.rel[, "calamity"])

summary(var.harv.dam.rev)
```

```
##
## VAR Estimation Results:
## =========================
## Endogenous variables: harvest.vol, share.wood.damaged, revenues
## Deterministic variables: const
## Sample size: 14
## Log Likelihood: 48.615
## Roots of the characteristic polynomial:
## 0.7999 0.7999 0.7911 0.7911 0.4001 0.4001
## Call:
## vars::VAR(y = as.ts(dat.spruce.rel[, c("harvest.vol", "share.wood.damaged",
##     "revenues")], start = 2005), p = 2, type = "const", exogen = dat.spruce.rel[,
##     "calamity"], ic = "AIC")
##
##
## Estimation results for equation harvest.vol:
## ============================================
## harvest.vol = harvest.vol.l1 + share.wood.damaged.l1 + revenues.l1 + harvest.vol.l2 + share.wood.dama
##
##                       Estimate Std. Error t value Pr(>|t|)
## harvest.vol.l1         0.07597    0.26475   0.287   0.7838
## share.wood.damaged.l1 -0.52571    1.09912  -0.478   0.6494
## revenues.l1           -4.21722    3.10801  -1.357   0.2236
## harvest.vol.l2        -0.11563    0.29272  -0.395   0.7065
## share.wood.damaged.l2 -1.30038    0.98374  -1.322   0.2344
## revenues.l2           -0.61819    1.82470  -0.339   0.7463
## const                  6.82412    2.86957   2.378   0.0549 .
## calamity               2.00001    0.63367   3.156   0.0197 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 0.5838 on 6 degrees of freedom
## Multiple R-Squared: 0.9193,  Adjusted R-squared: 0.8252
## F-statistic: 9.769 on 7 and 6 DF,  p-value: 0.006487
##
##
## Estimation results for equation share.wood.damaged:
## ===================================================
```

```
## share.wood.damaged = harvest.vol.l1 + share.wood.damaged.l1 + revenues.l1 + harvest.vol.l2 + share.wo
##
##                      Estimate Std. Error t value Pr(>|t|)
## harvest.vol.l1        0.02201    0.11713   0.188   0.8571
## share.wood.damaged.l1 -0.09319    0.48625  -0.192   0.8543
## revenues.l1          -1.72854    1.37498  -1.257   0.2554
## harvest.vol.l2        0.02576    0.12950   0.199   0.8489
## share.wood.damaged.l2 -0.57375    0.43520  -1.318   0.2355
## revenues.l2          -0.37859    0.80724  -0.469   0.6556
## const                 2.69158    1.26949   2.120   0.0783 .
## calamity              0.01181    0.28033   0.042   0.9678
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 0.2583 on 6 degrees of freedom
## Multiple R-Squared: 0.7229,  Adjusted R-squared: 0.3996
## F-statistic: 2.236 on 7 and 6 DF,  p-value: 0.1731
##
##
## Estimation results for equation revenues:
## =========================================
## revenues = harvest.vol.l1 + share.wood.damaged.l1 + revenues.l1 + harvest.vol.l2 + share.wood.damaged
##
##                      Estimate Std. Error t value Pr(>|t|)
## harvest.vol.l1       -0.05521    0.03644  -1.515   0.1805
## share.wood.damaged.l1  0.01483    0.15129   0.098   0.9251
## revenues.l1           0.76172    0.42780   1.781   0.1253
## harvest.vol.l2       -0.06094    0.04029  -1.513   0.1812
## share.wood.damaged.l2  0.12088    0.13541   0.893   0.4064
## revenues.l2          -0.48564    0.25116  -1.934   0.1013
## const                 0.76967    0.39498   1.949   0.0992 .
## calamity             -0.18139    0.08722  -2.080   0.0828 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 0.08036 on 6 degrees of freedom
## Multiple R-Squared: 0.9373,  Adjusted R-squared: 0.8641
## F-statistic: 12.81 on 7 and 6 DF,  p-value: 0.003158
##
##
##
## Covariance matrix of residuals:
##                   harvest.vol share.wood.damaged  revenues
## harvest.vol           0.34085            0.12935 -0.045346
## share.wood.damaged    0.12935            0.06671 -0.017734
## revenues             -0.04535           -0.01773  0.006458
##
## Correlation matrix of residuals:
##                   harvest.vol share.wood.damaged revenues
## harvest.vol            1.0000             0.8578  -0.9666
## share.wood.damaged     0.8578             1.0000  -0.8545
## revenues              -0.9666            -0.8545   1.0000
```

We compared the estimated coefficients and $adj.R^2$ for the three fitted VARs (Tab. 9). The model considering only the harvest volume showed the highest $adj.R^2$. Considering also the share of damaged volume (var.harv.dam.rev) only slightly altered the estimated coefficients as compared to the model without the share of damaged wood. We therefore concluded that the quality effect contributed, at most, only slightly to the explanatory power of the model, which was related to the harvest volume. This model with 3 time series was not considered in the main part of the publication as it delivers no additional information compared with the model with the 2 series harvest.vol and revenues and the higher model complexity is therefore not reasonable.

Table 9: Comparison of the fitted VAR models for average revenues considering different explanatory varibales: var.harv.rev: *harvest.vol*, var.dam.rev: *share.damaged.wood*, var.harv.dam.rev: *harvest.vol* and *share.damaged.wood*. NA for coefficients which were not considered in the respective model.

coefficient	var.harv.rev	var.dam.rev	var.harv.dam.rev
adj.r.squared	0.884	0.834	0.864
calamity	-0.202	-0.134	-0.181
const	0.902	0.459	0.770
harvest.vol.l1	-0.054	NA	-0.055
harvest.vol.l2	-0.040	NA	-0.061
revenues.l1	0.695	1.184	0.762
revenues.l2	-0.526	-0.650	-0.486
share.wood.damaged.l1	NA	-0.127	0.015
share.wood.damaged.l2	NA	0.039	0.121

V.2.2. Residual analysis

```
par(mfrow = c(2, 1))
pacf(resid(var.harv.dam.rev)[,"revenues"],
     main = "PACF of the Residuals")
acf(resid(var.harv.dam.rev)[,"revenues"],
    main = "ACF of the Residuals")
```

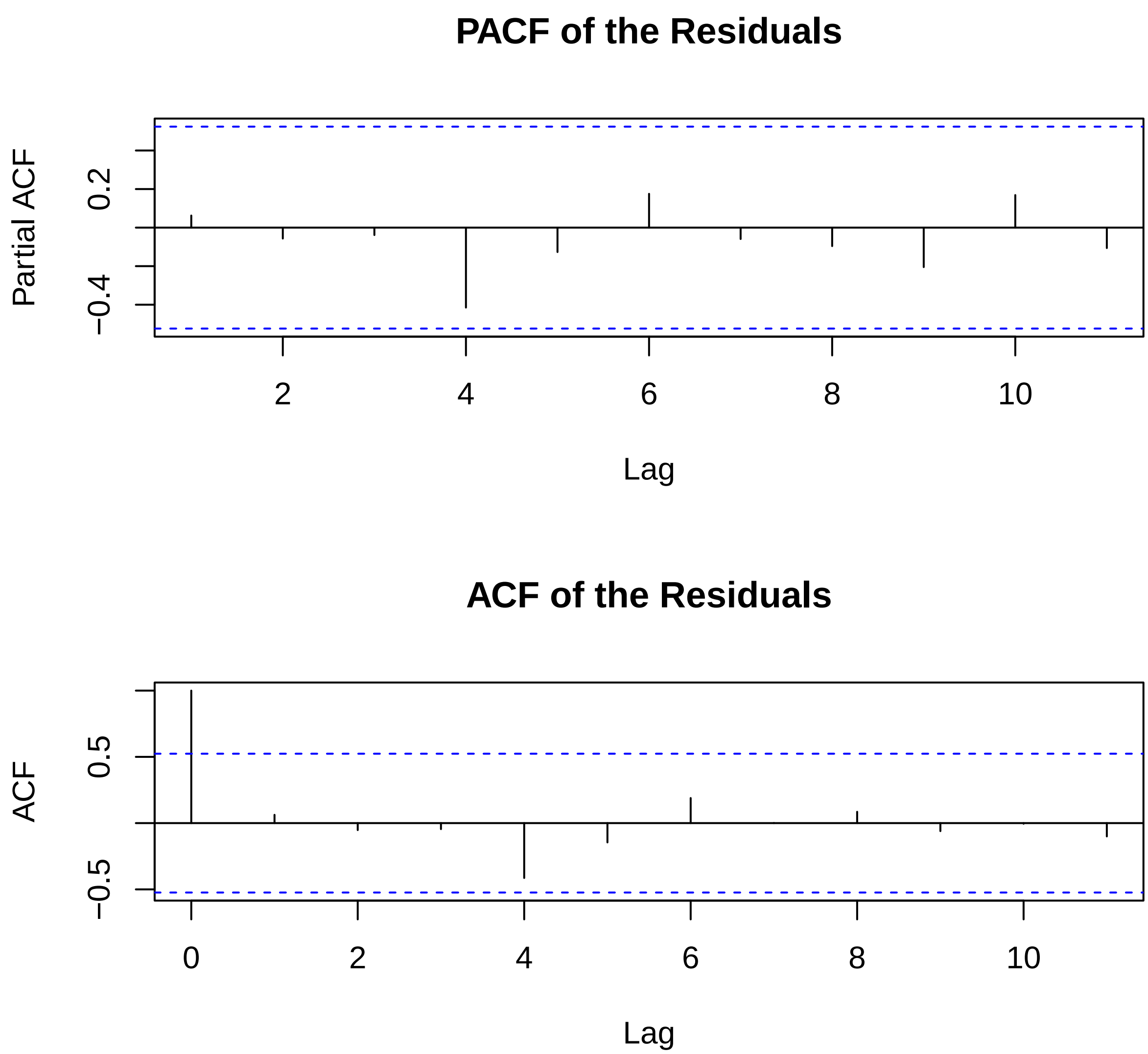

Figure 4: The autocorrelation function and the partial autocorrelation function reveal no remarkable autocorrelation of the model residuals. It can be followed that there is no evidence against our assumption of consistently estimated residuals.

V.3 SVAR and IRF

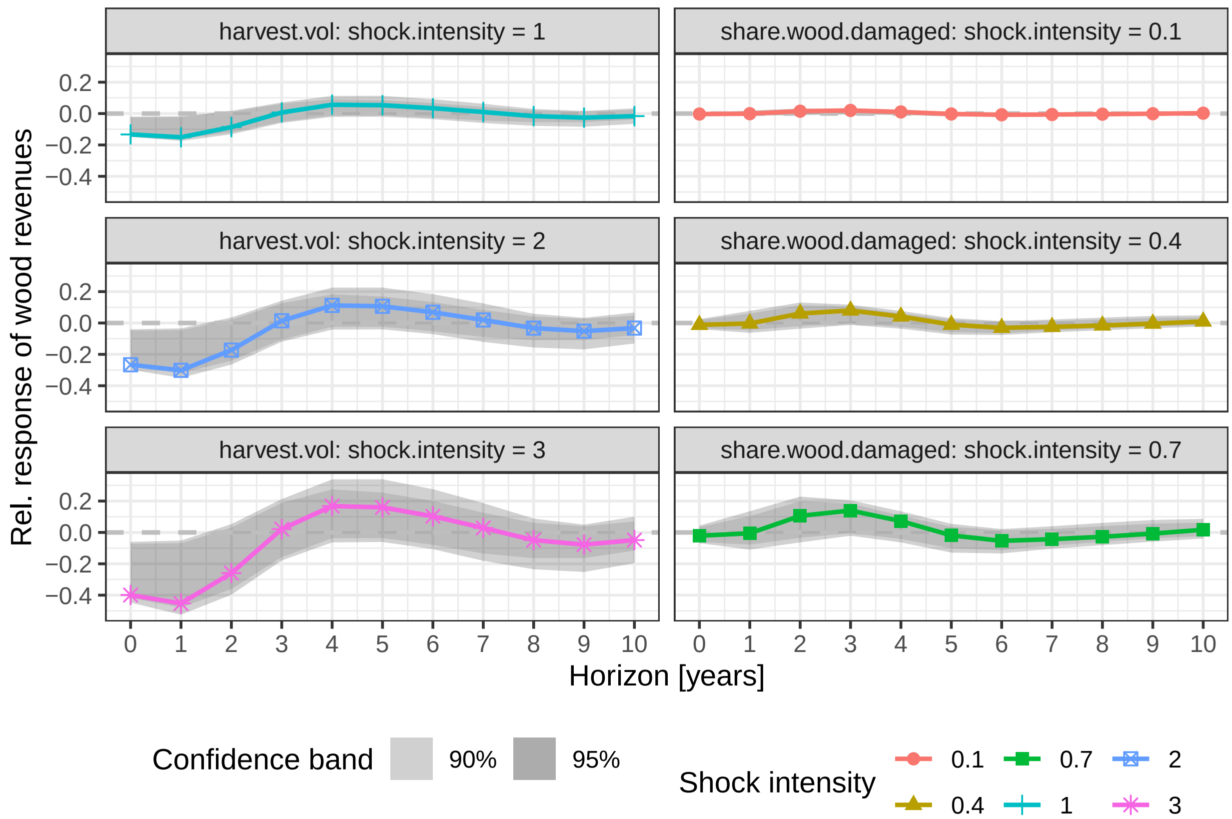

Figure 5: Impulse response of average revenues on shocks in the harvest volume (left panels) or share of damaged wood (right panels), respectively. Both derived based on a VAR with all three time series, but limited lag order (2 years).

One should consider that the presented IRFs based on all three time series had a maximum lag order of 2 years (due to the length of the time series) and our model selection suggested the simpler model based on the harvest volumes and revenues. Nevertheless, the findings based on the model with three time series support the findings presented in the results section, which are based on the VAR with harvest volumes and revenues.

VI. Correcting the revenues for the market effect

Although the models delivered no clear evidence for an effect of the share of damaged wood on revenues, we further sought to investigate this anticipated effect. We corrected the revenues for the market effect to isolate the quality effect. To do so, we assumed that the market effect is comparable between the different assortments and linked to the development of revenues of a so-called 'reference assortment'. The reference assortment for spruce in Hesse are sawlogs of $20-29$ cm diameter in the middle of the log and of good quality (B on a scale from A to D, with A being the best quality). An assortment is defined as a homogeneous good – its revenues' development should thus solely be driven by effects of supply and demand on the wood markets rather than quality changes. The development of this reference assortment's revenue index ($revenues.ref.ass$, calculated based on the Hessian revenue data) is therefore interpreted as the pure market effect. We used it to correct the development of average wood revenues ($revenues$, see previous analyses) in order to extract the quality effect ($revenues.market.corr$):

$$revenues.market.corr = \frac{revenues}{revenues.ref.ass} \tag{1}$$

```
dat.spruce.qual <- dat.spruce.rel %>%
  mutate(revenues.market.corr = revenues / revenues.ref.ass)

summary(dat.spruce.qual$revenues.market.corr)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.9151  0.9949  1.0028  1.0013  1.0193  1.0604
```

The analysis suggested that there might be further effects influencing the wood revenues, which are, however, of minor importance compared to the market effect - but certainly worth investigating in further research. Particularly the years 2018 and 2020 seemed to be influenced by changes in the average quality of the sold wood. More detailed analyses of the data revealed that this is mainly caused by a higher share of pulpwood compared to, e.g., 2007 or 2019. In this case, market-corrected revenues decreased by about 8 %. Nevertheless, one can conclude that the effect of quality on spruce revenues is much smaller than that of oversupply and not statistically consolidated.

This finding also supports the results of our model selection, where we identified harvest volumes as a key variable in describing revenues. It further indicates that a possible collinearity between harvest volumes and shares of damaged wood is of limited importance to our results and conclusions from the models based on the harvest volumes.

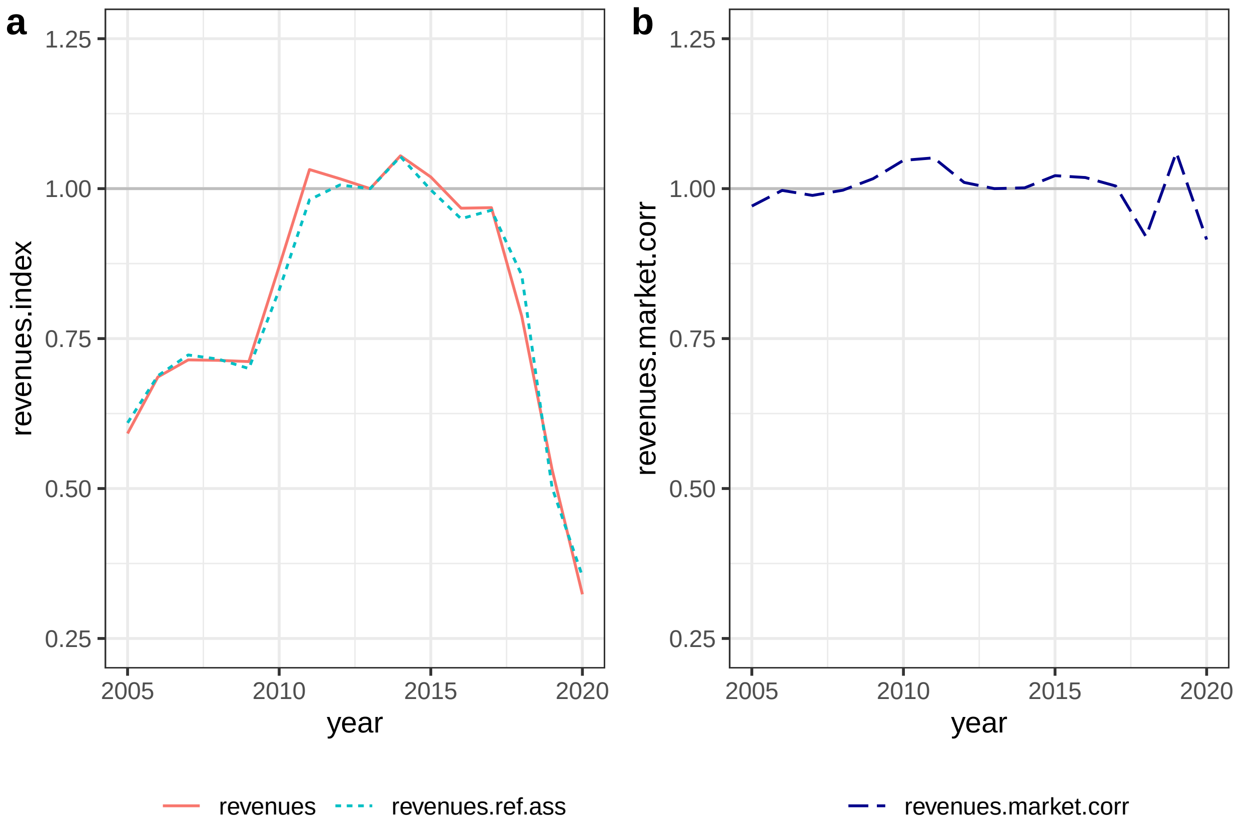

Figure 6: Relative development of avarage revenues (revenues) as well as revenues of a reference assortment (revenues.ref.ass) (a) and the development of average revenues corrected for the market effect (b).

VII. Time series of pulpwood and sawlog proportions

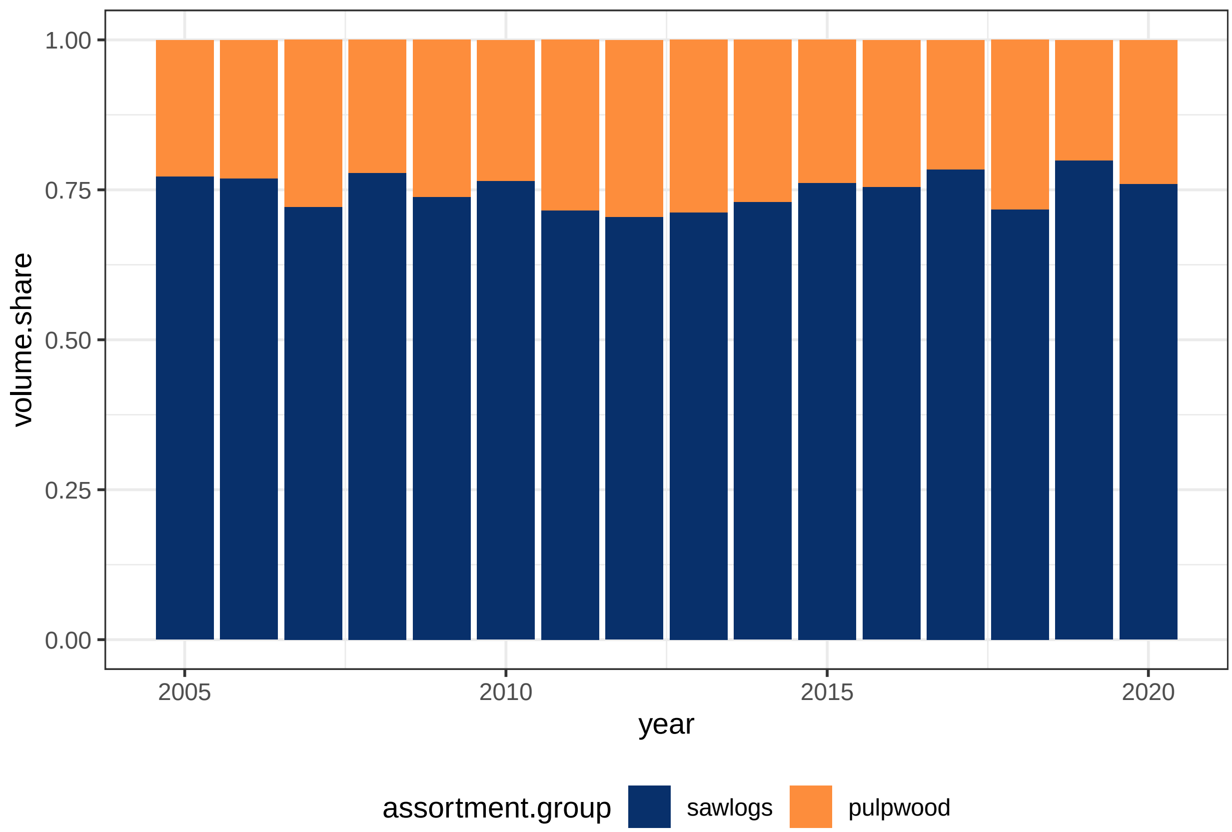

Figure 7: Time series of relative shares of sawlog and pulpwood assortments sold.

Supplement B: Detailed analyses beech

Supplementary material to *Quantifying the consequences of disturbances on wood revenues with Impulse Response Functions*

Contents

I. Pre-analyses of the data sets

```
library(tidyverse)
library(tseries)
library(vars)
library(kableExtra)
```

I.1. Lag order selection harvest and sale volumes

We tested whether there is evidence for any time lag between the annual volumes of harvests and sales. For this, we conducted a lag order selection testing a maximum lag order lag.max = 2.

```
lago.vol <- VARselect(dat.beech.rel[, c("harvest.vol",
                                        "sale.vol")],
                      type = "const",
                      lag.max = 2,
                      exo = dat.beech.rel[, "calamity"])
```

Table 1: Lag order selection (lag.order in years) of harvest volume and sale volume based on 4 selection criteria.

criterion	lag.order
AIC	2
HQ	2
SC	2
FPE	2

All criteria suggested a lag order > 0 (Tab. 1), which confirmed that the series had inter-annual relationships. Therefore, we applied methods of time series analysis for the subsequent analyses.

I.2. Correlations

Table 2: Correlations between the variables.

	revenues	harvest.vol	share.wood.damaged
revenues	1.00	0.02	0.09
harvest.vol	0.02	1.00	-0.23
share.wood.damaged	0.09	-0.23	1.00

II. Market effect

II.1. Model selection

We selected the VAR model based on two lag order selections with lag orders of up to only 3 years, as our time series had a length of only 16 years. Higher lag orders could have led close to a saturated model. Restricting the lag order also reduced potential problems with multicollinearity. We tested models with and without the dummy variable for years with transregional calamities.

```r
# without dummy
lago.harv.rev <- VARselect(
  dat.beech.rel[, c("harvest.vol",
                    "revenues")],
  type = "const",
  lag.max = 3)

# with dummy
lago.harv.rev.dummy <- VARselect(
  dat.beech.rel[, c("harvest.vol",
                    "revenues")],
  type = "const",
  lag.max = 3,
  exo = dat.beech.rel[, "calamity"])
```

Table 3: Lag order selection (lag order in years) of harvest volume and average wood revenues based on 4 selection criteria. Tested for 3 years at maximum.

model	AIC	FPE	HQ	SC
lag order 3 +dummy	-12.1	8.0e-06	-12.28	-11.44
lag order 3	-11.6	1.1e-05	-11.76	-11.03
lag order 2 +dummy	-11.2	1.6e-05	-11.28	-10.65
lag order 2	-11.0	1.8e-05	-11.07	-10.55
lag order 1 +dummy	-10.5	2.8e-05	-10.58	-10.16
lag order 1	-10.2	3.9e-05	-10.23	-9.91

All criteria suggested a time lag of 3 years and considering the dummy variable for calamity years (Tab. 3).

II.2. VAR

II.2.1. VAR estimation

We fitted a VAR according to the model selection to determine the effect of the harvest volume (market effect) on wood revenues.

```
var.harv.rev <- vars::VAR(
  as.ts(dat.beech.rel[, c("harvest.vol",
                          "revenues")],
        start = 2005),
  p = 3,
  type = "const",
  ic = "AIC",
  exogen = dat.beech.rel[, "calamity"])

summary(var.harv.rev)
```

```
##
## VAR Estimation Results:
## =========================
## Endogenous variables: harvest.vol, revenues
## Deterministic variables: const
## Sample size: 13
## Log Likelihood: 57.985
## Roots of the characteristic polynomial:
## 0.8297 0.8297 0.7541 0.7541 0.598 0.349
## Call:
## vars::VAR(y = as.ts(dat.beech.rel[, c("harvest.vol", "revenues")],
##     start = 2005), p = 3, type = "const", exogen = dat.beech.rel[,
##     "calamity"], ic = "AIC")
##
##
## Estimation results for equation harvest.vol:
## ============================================
## harvest.vol = harvest.vol.l1 + revenues.l1 + harvest.vol.l2 + revenues.l2 + harvest.vol.l3 + revenues
##
##                 Estimate Std. Error t value Pr(>|t|)
## harvest.vol.l1  0.821001   0.305103   2.691  0.04325 *
## revenues.l1    -2.383067   0.683929  -3.484  0.01758 *
## harvest.vol.l2  0.003732   0.264761   0.014  0.98930
## revenues.l2    -0.143750   0.656470  -0.219  0.83533
## harvest.vol.l3 -0.175156   0.162225  -1.080  0.32958
## revenues.l3     0.956674   0.425131   2.250  0.07425 .
## const           1.964901   0.474735   4.139  0.00901 **
## calamity       -0.213422   0.087471  -2.440  0.05866 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 0.059 on 5 degrees of freedom
## Multiple R-Squared: 0.9658,  Adjusted R-squared: 0.9178
## F-statistic: 20.15 on 7 and 5 DF,  p-value: 0.002214
##
##
## Estimation results for equation revenues:
```

```
## ========================================
## revenues = harvest.vol.l1 + revenues.l1 + harvest.vol.l2 + revenues.l2 + harvest.vol.l3 + revenues.l3
##
##                Estimate Std. Error t value Pr(>|t|)
## harvest.vol.l1  0.16477    0.16609   0.992   0.3667
## revenues.l1    -0.17897    0.37231  -0.481   0.6510
## harvest.vol.l2  0.11762    0.14413   0.816   0.4516
## revenues.l2    -0.47718    0.35736  -1.335   0.2393
## harvest.vol.l3 -0.01347    0.08831  -0.153   0.8847
## revenues.l3     0.54005    0.23143   2.334   0.0669 .
## const           0.90038    0.25843   3.484   0.0176 *
## calamity        0.02231    0.04762   0.468   0.6592
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 0.03212 on 5 degrees of freedom
## Multiple R-Squared: 0.825,   Adjusted R-squared:  0.58
## F-statistic: 3.367 on 7 and 5 DF,  p-value: 0.1
##
##
##
## Covariance matrix of residuals:
##             harvest.vol   revenues
## harvest.vol   0.0034807 -0.0007032
## revenues     -0.0007032  0.0010315
##
## Correlation matrix of residuals:
##             harvest.vol revenues
## harvest.vol      1.0000  -0.3711
## revenues        -0.3711   1.0000
```

II.2.2. Residual analysis

```
par(mfrow = c(2, 1))
pacf(resid(var.harv.rev)[,"revenues"],
     main = "PACF of the Residuals")
acf(resid(var.harv.rev)[,"revenues"],
    main = "ACF of the Residuals")
```

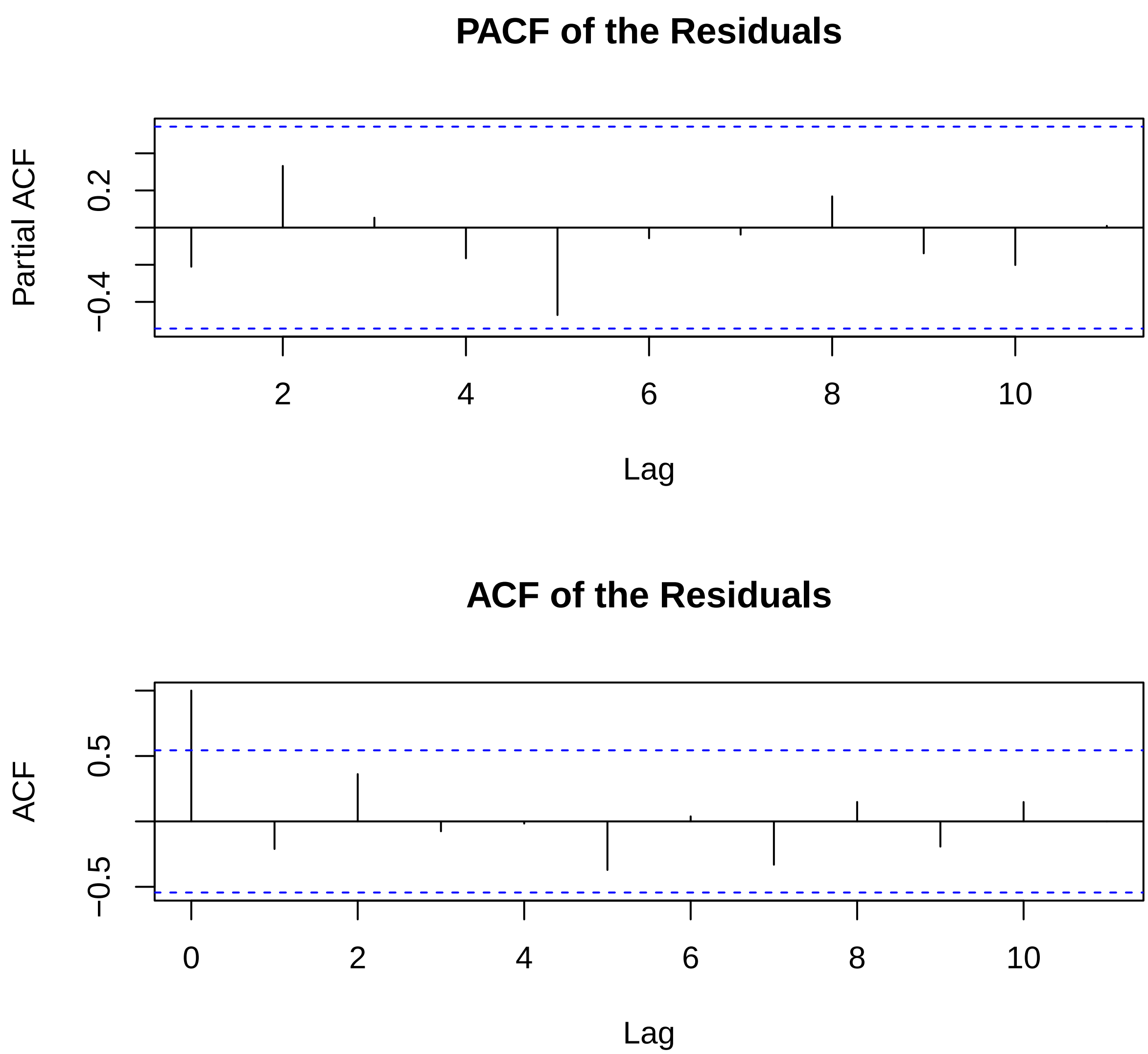

Figure 1: The autocorrelation function and the partial autocorrelation function reveal no remarkable autocorrelation of the model residuals. It can be followed that there is no evidence against our assumption of consistently estimated residuals.

II.3. SVAR and IRF

Based on the estimated reduced-form VAR, we derived IRFs for shocks of varying intensity.

```
shock.intensities <- seq(0.1, 0.3, 0.1)

dat.harv.rev.plot <- tibble()

var.harv.rev.irf.orig <- vars::irf(
  var.harv.rev,
  n.ahead = 10,
  ci = 0.95,
  runs = 2000,
  ortho = TRUE)

for (i in shock.intensities) {

  var.harv.rev.irf <- var.harv.rev.irf.orig

  # rescaling the IRF to modify the shock intensity
  # (identical to modifying the B matrix as described in the manuscript)
  var.harv.rev.irf$irf$harvest.vol <-
    (var.harv.rev.irf.orig$irf$harvest.vol /
       var.harv.rev.irf.orig$irf$harvest.vol[1, 1]) * i

  dat.harv.rev.plot <- dat.harv.rev.plot %>%
    bind_rows(
      c(shock.intensity = i,
        corr.factor = 1 /
          var.harv.rev.irf.orig$irf$harvest.vol[1, 1] * i,
        var.harv.rev.irf$irf$harvest.vol[, 2])
    )

}
```

Table 4: Impulse response of revenues on shocks in the harvest volume. The shock intensity denotes the magnitude of the additional harvested volume in relation to the harvest volume in 2013. The maximum observed shock in the time series was about 0.24.

horizon	shock.intensity = 0.1	shock.intensity = 0.2	shock.intensity = 0.3
0	-0.020	-0.040	-0.061
1	0.020	0.040	0.060
2	0.039	0.079	0.118
3	-0.003	-0.007	-0.010
4	-0.015	-0.030	-0.046
5	0.004	0.008	0.011
6	-0.001	-0.002	-0.003
7	-0.006	-0.013	-0.019
8	0.006	0.012	0.018
9	0.006	0.012	0.019
10	-0.004	-0.008	-0.012

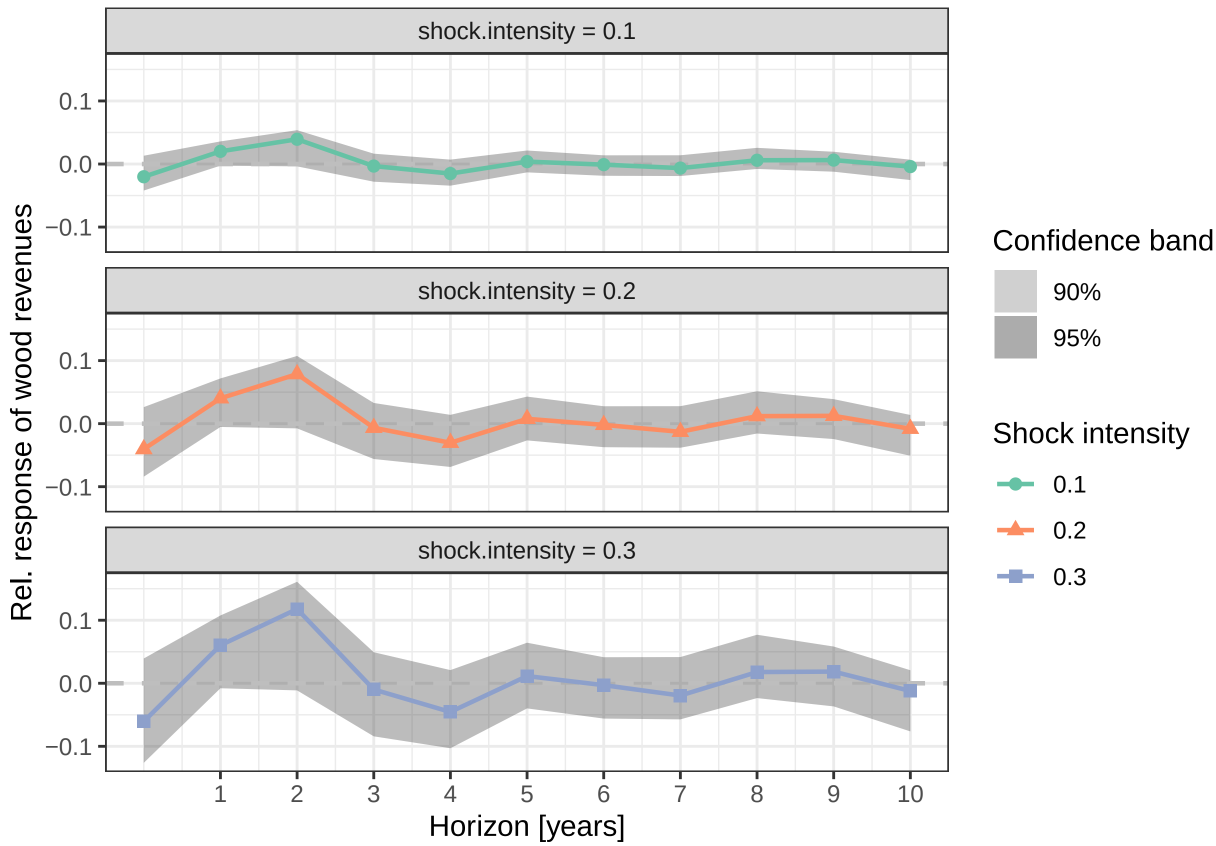

Figure 2: Impulse response of revenues on shocks in the harvest volume. The shock intensity denotes the magnitude of the additional harvested volume in relation to the harvest volume in 2013. The maximum observed shock in the time series was about 0.24.

III Quality effect

III.1. Model selection

In line with the VAR analysis on the harvest volume, we selected the VAR model for the share of damaged wood based on two lag order selections with lag orders up to 3 years, and tested models with and without a dummy variable for large-scale calamities.

```
# without dummy
lago.harv.rev <- VARselect(
  dat.beech.rel[, c("share.wood.damaged",
                    "revenues")],
  type = "const",
  lag.max = 3)

# with dummy
lago.harv.rev.dummy <- VARselect(
  dat.beech.rel[, c("share.wood.damaged",
                    "revenues")],
  type = "const",
  lag.max = 3,
  exo = dat.beech.rel[, "calamity"])
```

Table 5: Lag order selection (lag order in years) of share of damaged wood and average wood revenues based on 4 selection criteria. Tested for 3 years at maximum.

model	AIC	FPE	HQ	SC
lag order 3 +dummy	-12.5	6.0e-06	-12.60	-11.76
lag order 2 +dummy	-12.4	5.0e-06	-12.47	-11.84
lag order 2	-12.2	5.0e-06	-12.32	-11.79
lag order 3	-12.0	8.0e-06	-12.13	-11.40
lag order 1 +dummy	-10.6	2.5e-05	-10.71	-10.29
lag order 1	-9.9	5.2e-05	-9.93	-9.61

All criteria suggested a lag order of 2-3 years and considering the calamity dummy (Tab. 5). We followed the AIC and chose 3 years.

III.2. VAR

III.2.1. VAR estimation

We fitted a VAR according to the model selection to determine the effect of the share of damaged wood (quality effect) on wood revenues.

```
var.dam.rev <- vars::VAR(
  as.ts(dat.beech.rel[, c("share.wood.damaged",
                          "revenues")],
        start = 2005),
  p = 3,
  type = "const",
  ic = "AIC",
  exogen = dat.beech.rel[, "calamity"])

summary(var.dam.rev)
```

```
##
## VAR Estimation Results:
## =========================
## Endogenous variables: share.wood.damaged, revenues
## Deterministic variables: const
## Sample size: 13
## Log Likelihood: 60.047
## Roots of the characteristic polynomial:
## 0.849 0.7503 0.7503 0.6495 0.6495 0.5208
## Call:
## vars::VAR(y = as.ts(dat.beech.rel[, c("share.wood.damaged", "revenues")],
##     start = 2005), p = 3, type = "const", exogen = dat.beech.rel[,
##     "calamity"], ic = "AIC")
##
##
## Estimation results for equation share.wood.damaged:
## ===================================================
## share.wood.damaged = share.wood.damaged.l1 + revenues.l1 + share.wood.damaged.l2 + revenues.l2 + sha
##
##                        Estimate Std. Error t value Pr(>|t|)
## share.wood.damaged.l1  0.210594   0.645622   0.326   0.7575
## revenues.l1           -2.128039   1.195124  -1.781   0.1351
## share.wood.damaged.l2 -0.006083   0.274968  -0.022   0.9832
## revenues.l2            1.143802   0.673193   1.699   0.1501
## share.wood.damaged.l3 -0.502499   0.446737  -1.125   0.3117
## revenues.l3           -0.647735   0.471571  -1.374   0.2280
## const                  1.807240   1.682786   1.074   0.3319
## calamity               0.256782   0.108150   2.374   0.0636 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 0.07204 on 5 degrees of freedom
## Multiple R-Squared: 0.8451,  Adjusted R-squared: 0.6283
## F-statistic: 3.898 on 7 and 5 DF,  p-value: 0.07669
##
##
## Estimation results for equation revenues:
```

```
## ========================================
## revenues = share.wood.damaged.l1 + revenues.l1 + share.wood.damaged.l2 + revenues.l2 + share.wood.da
##
##                       Estimate Std. Error t value Pr(>|t|)
## share.wood.damaged.l1 -0.209448   0.186790  -1.121   0.3131
## revenues.l1           -0.125266   0.345771  -0.362   0.7320
## share.wood.damaged.l2 -0.284921   0.079553  -3.582   0.0158 *
## revenues.l2           -0.414849   0.194767  -2.130   0.0864 .
## share.wood.damaged.l3 -0.164527   0.129249  -1.273   0.2590
## revenues.l3           -0.003144   0.136434  -0.023   0.9825
## const                  1.661845   0.486860   3.413   0.0190 *
## calamity               0.002883   0.031290   0.092   0.9302
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 0.02084 on 5 degrees of freedom
## Multiple R-Squared: 0.9263,  Adjusted R-squared: 0.8231
## F-statistic: 8.976 on 7 and 5 DF,  p-value: 0.01401
##
##
##
## Covariance matrix of residuals:
##                    share.wood.damaged  revenues
## share.wood.damaged          5.190e-03 2.927e-05
## revenues                    2.927e-05 4.345e-04
##
## Correlation matrix of residuals:
##                    share.wood.damaged revenues
## share.wood.damaged            1.00000  0.01949
## revenues                      0.01949  1.00000
```

III.2.2. Residual analysis

```r
par(mfrow = c(2, 1))
pacf(resid(var.dam.rev)[,"revenues"],
     main = "PACF of the Residuals")
acf(resid(var.dam.rev)[,"revenues"],
    main = "ACF of the Residuals")
```

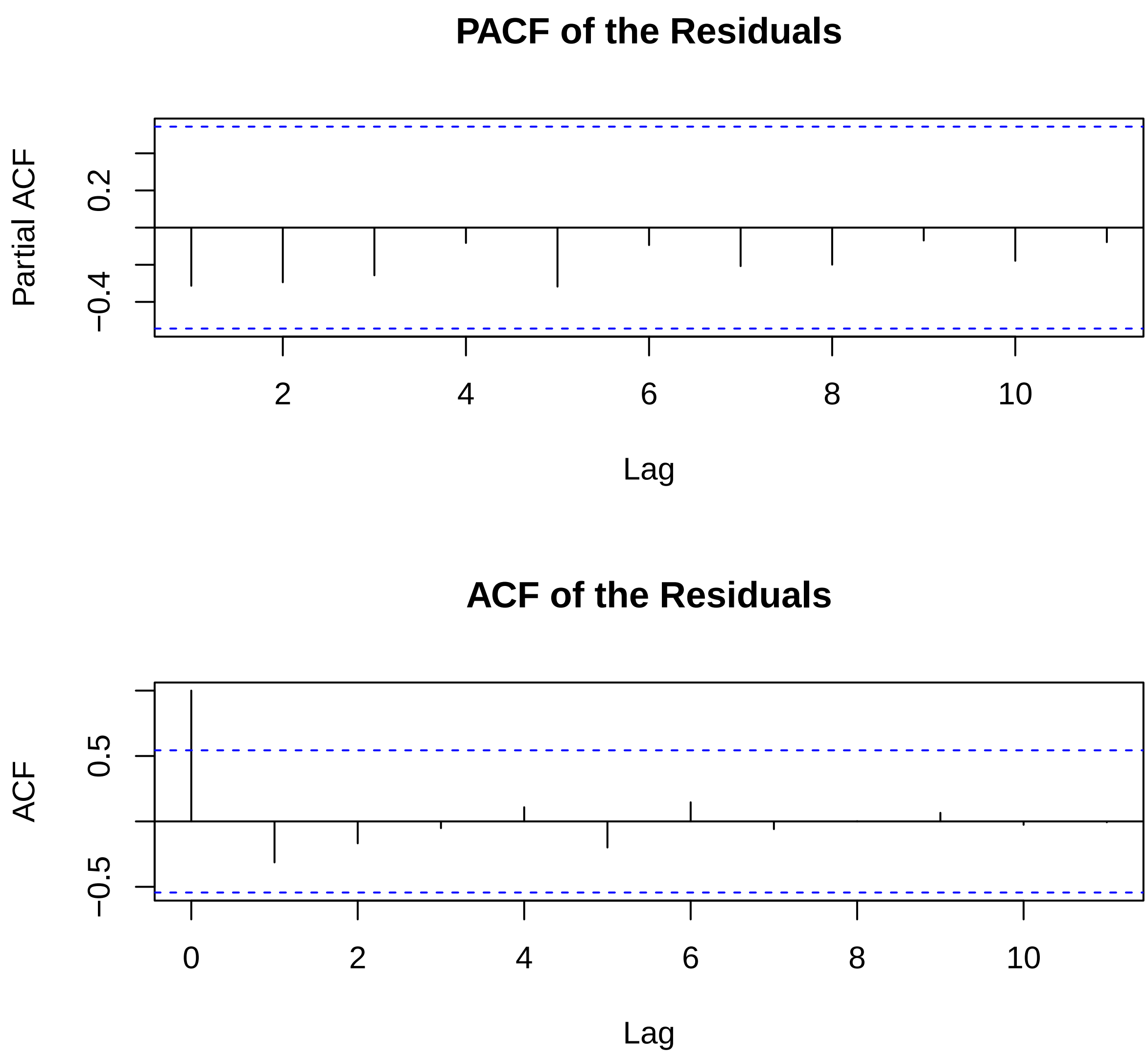

Figure 3: The autocorrelation function and the partial autocorrelation function reveal no remarkable autocorrelation of the model residuals. It can be followed that there is no evidence against our assumption of consistently estimated residuals.

III.3. SVAR and IRF

Based on the estimated reduced-form VAR, we derived IRFs for shocks of varying intensity.

```
shock.intensities <- seq(0.1, 0.3, 0.1)

dat.dam.rev.plot <- tibble()

var.dam.rev.irf.orig <- vars::irf(
  var.dam.rev,
  n.ahead = 10,
  ci = 0.95,
  runs = 2000,
  ortho = TRUE)

for (i in shock.intensities) {

  var.dam.rev.irf <- var.dam.rev.irf.orig

  # rescaling the IRF to modify the shock intensity
  # (identical to modifying the B matrix as described in the manuscript)
  var.dam.rev.irf$irf$share.wood.damaged <-
    (var.dam.rev.irf.orig$irf$share.wood.damaged /
       var.dam.rev.irf.orig$irf$share.wood.damaged[1, 1]) *
    i

  dat.dam.rev.plot <- dat.dam.rev.plot %>%
    bind_rows(
      c(shock.intensity = i,
        corr.factor = 1 /
          var.dam.rev.irf.orig$irf$share.wood.damaged[1, 1] *
          i,
        var.dam.rev.irf$irf$share.wood.damaged[, 2])
    )

}
```

Table 6: Impulse response of revenues on shocks in the share of damaged wood. The shock intensity denotes the magnitude of the additional share of damaged wood. The maximum observed, additional share of damaged wood to the non-calamity situation (2013) was about 0.38.

horizon	shock.intensity = 0.1	shock.intensity = 0.2	shock.intensity = 0.3
0	0.001	0.001	0.002
1	-0.021	-0.042	-0.063
2	-0.030	-0.061	-0.091
3	-0.020	-0.040	-0.060
4	-0.002	-0.004	-0.006
5	-0.002	-0.003	-0.005
6	0.002	0.005	0.007
7	0.003	0.005	0.008
8	0.001	0.003	0.004
9	-0.002	-0.003	-0.005
10	0.000	0.000	0.000

For the results, see also Figure 3 in the main text.

IV. Granger causality

Linear hypothesis test, whether the harvest volume or the share of damaged wood Granger-causes revenues.

```
causality(var.harv.rev, cause = "harvest.vol")$Granger
```

```
##
##  Granger causality H0: harvest.vol do not Granger-cause revenues
##
## data:  VAR object var.harv.rev
## F-Test = 1.4548, df1 = 3, df2 = 10, p-value = 0.285
```

```
causality(var.dam.rev, cause = "share.wood.damaged")$Granger
```

```
##
##  Granger causality H0: share.wood.damaged do not Granger-cause revenues
##
## data:  VAR object var.dam.rev
## F-Test = 5.744, df1 = 3, df2 = 10, p-value = 0.01505
```

V. Combined market and quality effect

We also tested a VAR combining the effects of the harvest volume and share of damaged wood on revenues in one model.

V.1. Model selection

Due to the limited length of the time series, we tested a maximum lag order of 2 when considering 3 time series in one model.

```
lago.harv.dam.rev <- VARselect(dat.beech.rel[, c("harvest.vol",
                                                  "share.wood.damaged",
                                                  "revenues")],
                               type = "const",
                               lag.max = 2,
                               exogen = dat.beech.rel[, "calamity"])
```

Table 7: Lag order selection (lag order in years) of harvest volume, share of damaged wood, and wood revenues based on 4 selection criteria. Tested for 2 years at maximum.

model	AIC	FPE	HQ	SC
lag order 2	-17.2	0e+00	-17.35	-16.15
lag order 1	-15.8	2e-07	-15.90	-15.15

All criteria suggested a time lag of 2 years (Tab. 7).

V.2. VAR

V.2.1 VAR estimation

```r
var.harv.dam.rev <- vars::VAR(
  as.ts(dat.beech.rel[, c("harvest.vol",
                          "share.wood.damaged",
                          "revenues")],
        start = 2005),
  p = 2,
  type = "const",
  ic = "AIC",
  exogen = dat.beech.rel[, "calamity"])

summary(var.harv.dam.rev)
```

```
##
## VAR Estimation Results:
## =========================
## Endogenous variables: harvest.vol, share.wood.damaged, revenues
## Deterministic variables: const
## Sample size: 14
## Log Likelihood: 85.14
## Roots of the characteristic polynomial:
## 0.7554 0.7554 0.7144 0.6868 0.6868 0.2393
## Call:
## vars::VAR(y = as.ts(dat.beech.rel[, c("harvest.vol", "share.wood.damaged",
##     "revenues")], start = 2005), p = 2, type = "const", exogen = dat.beech.rel[,
##     "calamity"], ic = "AIC")
##
##
## Estimation results for equation harvest.vol:
## ============================================
## harvest.vol = harvest.vol.l1 + share.wood.damaged.l1 + revenues.l1 + harvest.vol.l2 + share.wood.dama
##
##                        Estimate Std. Error t value Pr(>|t|)
## harvest.vol.l1          0.64915    0.42449   1.529  0.17707
## share.wood.damaged.l1 -0.21726    0.47067  -0.462  0.66063
## revenues.l1           -1.45692    0.86012  -1.694  0.14123
## harvest.vol.l2        -0.40788    0.18628  -2.190  0.07111 .
## share.wood.damaged.l2 -0.39706    0.25034  -1.586  0.16381
## revenues.l2            0.04716    1.09902   0.043  0.96716
## const                  2.24101    0.69630   3.218  0.01817 *
## calamity              -0.26344    0.06242  -4.220  0.00556 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 0.07315 on 6 degrees of freedom
## Multiple R-Squared: 0.949,   Adjusted R-squared: 0.8896
## F-statistic: 15.96 on 7 and 6 DF,  p-value: 0.001734
##
##
## Estimation results for equation share.wood.damaged:
## ===================================================
```

```
## share.wood.damaged = harvest.vol.l1 + share.wood.damaged.l1 + revenues.l1 + harvest.vol.l2 + share.wo
##
##                      Estimate Std. Error t value Pr(>|t|)
## harvest.vol.l1       -0.45571    0.40982  -1.112   0.3087
## share.wood.damaged.l1 -0.03048    0.45441  -0.067   0.9487
## revenues.l1          -0.23643    0.83040  -0.285   0.7854
## harvest.vol.l2        0.24944    0.17984   1.387   0.2148
## share.wood.damaged.l2 -0.05238    0.24169  -0.217   0.8356
## revenues.l2          -0.63368    1.06105  -0.597   0.5722
## const                 1.18702    0.67224   1.766   0.1279
## calamity              0.21487    0.06026   3.565   0.0118 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 0.07062 on 6 degrees of freedom
## Multiple R-Squared: 0.8819,  Adjusted R-squared: 0.7441
## F-statistic: 6.401 on 7 and 6 DF,  p-value: 0.01888
##
##
## Estimation results for equation revenues:
## =========================================
## revenues = harvest.vol.l1 + share.wood.damaged.l1 + revenues.l1 + harvest.vol.l2 + share.wood.damaged
##
##                      Estimate Std. Error t value Pr(>|t|)
## harvest.vol.l1        0.03392    0.13368   0.254  0.80817
## share.wood.damaged.l1  0.06283    0.14823   0.424  0.68642
## revenues.l1           0.35557    0.27088   1.313  0.23727
## harvest.vol.l2       -0.07695    0.05866  -1.312  0.23756
## share.wood.damaged.l2 -0.34744    0.07884  -4.407  0.00453 **
## revenues.l2          -0.16736    0.34611  -0.484  0.64584
## const                 0.91519    0.21928   4.174  0.00586 **
## calamity             -0.03760    0.01966  -1.913  0.10431
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 0.02304 on 6 degrees of freedom
## Multiple R-Squared: 0.8994,  Adjusted R-squared: 0.782
## F-statistic: 7.663 on 7 and 6 DF,  p-value: 0.01209
##
##
##
## Covariance matrix of residuals:
##                    harvest.vol share.wood.damaged  revenues
## harvest.vol          0.0053510         -0.0004704 0.0001818
## share.wood.damaged  -0.0004704          0.0049877 0.0003110
## revenues             0.0001818          0.0003110 0.0005307
##
## Correlation matrix of residuals:
##                    harvest.vol share.wood.damaged revenues
## harvest.vol            1.00000           -0.09106   0.1079
## share.wood.damaged    -0.09106            1.00000   0.1912
## revenues               0.10785            0.19115   1.0000
```

We compared the estimated coefficients and $adj.R^2$ for the three fitted VARs (Tab. 8). The model considering only the share of damaged wood showed the highest $adj.R^2$. Considering also the harvest volume (*var.harv.dam.rev*) suggested that the share of damaged wood is the most important influence on wood revenues of beech. When comparing the estimated coefficients, one should consider that *var.harv.rev* and *var.dam.rev* were calculated with a log order of 3, while the highest possible lag order that could be estimated for *var.harv.dam.rev* was 2.

Table 8: Comparison of the fitted VAR models for the average revenues considering different explanatory varibales: var.harv.rev: *harvest.vol*, var.dam.rev: *share.damaged.wood*, var.harv.dam.rev: *harvest.vol* and *share.damaged.wood*. NA for coefficients that were not considered in the respective model.

coefficient	var.harv.rev	var.dam.rev	var.harv.dam.rev
adj.r.squared	0.580	0.823	0.782
calamity	0.022	0.003	-0.038
const	0.900	1.662	0.915
harvest.vol.l1	0.165	NA	0.034
harvest.vol.l2	0.118	NA	-0.077
harvest.vol.l3	-0.013	NA	NA
revenues.l1	-0.179	-0.125	0.356
revenues.l2	-0.477	-0.415	-0.167
revenues.l3	0.540	-0.003	NA
share.wood.damaged.l1	NA	-0.209	0.063
share.wood.damaged.l2	NA	-0.285	-0.347
share.wood.damaged.l3	NA	-0.165	NA

V.2.2. Residual analysis

```
par(mfrow = c(2, 1))
pacf(resid(var.harv.dam.rev)[,"revenues"],
     main = "PACF of the Residuals")
acf(resid(var.harv.dam.rev)[,"revenues"],
    main = "ACF of the Residuals")
```

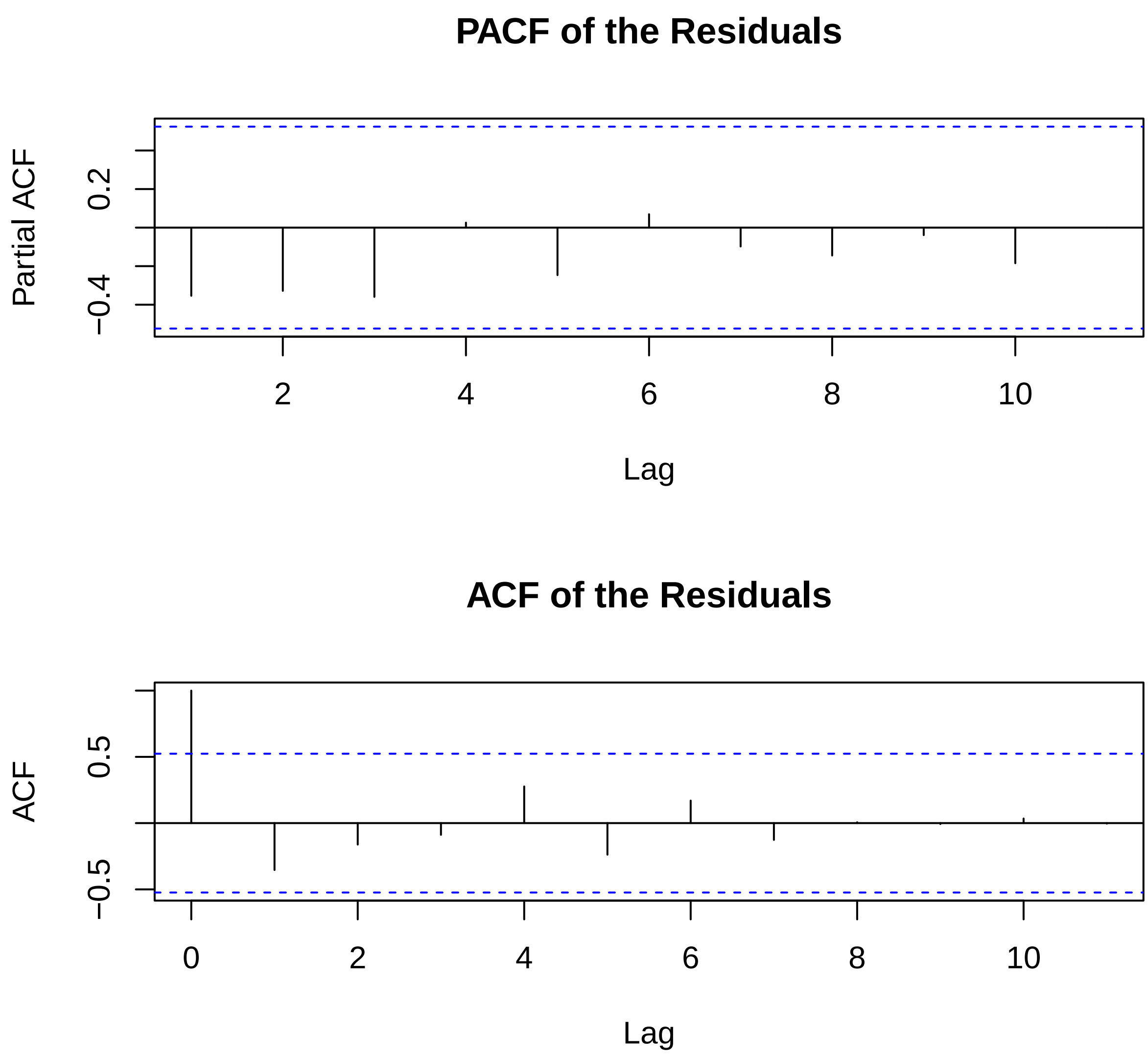

Figure 4: The autocorrelation function and the partial autocorrelation function reveal no remarkable autocorrelation of the model residuals. It can be followed that there is no evidence against our assumption of consistently estimated residuals.

V.3 SVAR and IRF

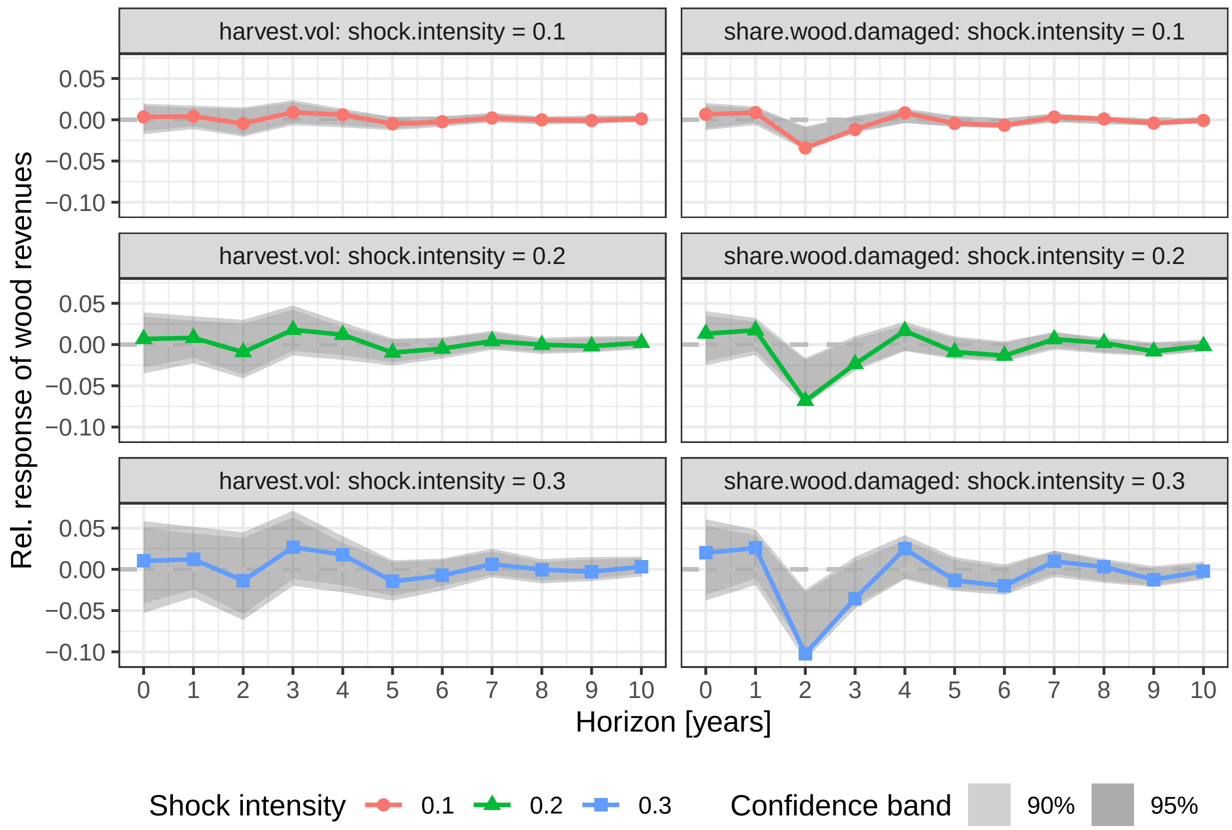

Figure 5: Impulse response of average revenues on shocks in the harvest volume (left panels) or share of damaged wood (right panels), respectively. Both derived based on a VAR with all three time series, but limited lag order (2 years).

One should consider that the presented IRFs based on all three time series had a maximum lag order of 2 years (due to the length of the time series) and our model selection suggested the simpler model based on the shares of damaged wood and revenues. Nevertheless, the findings based on the model with three time series support the findings presented in the results section, which are based on the VAR with shares of damaged wood and revenues.

VI. Time series of pulpwood and sawlog proportions

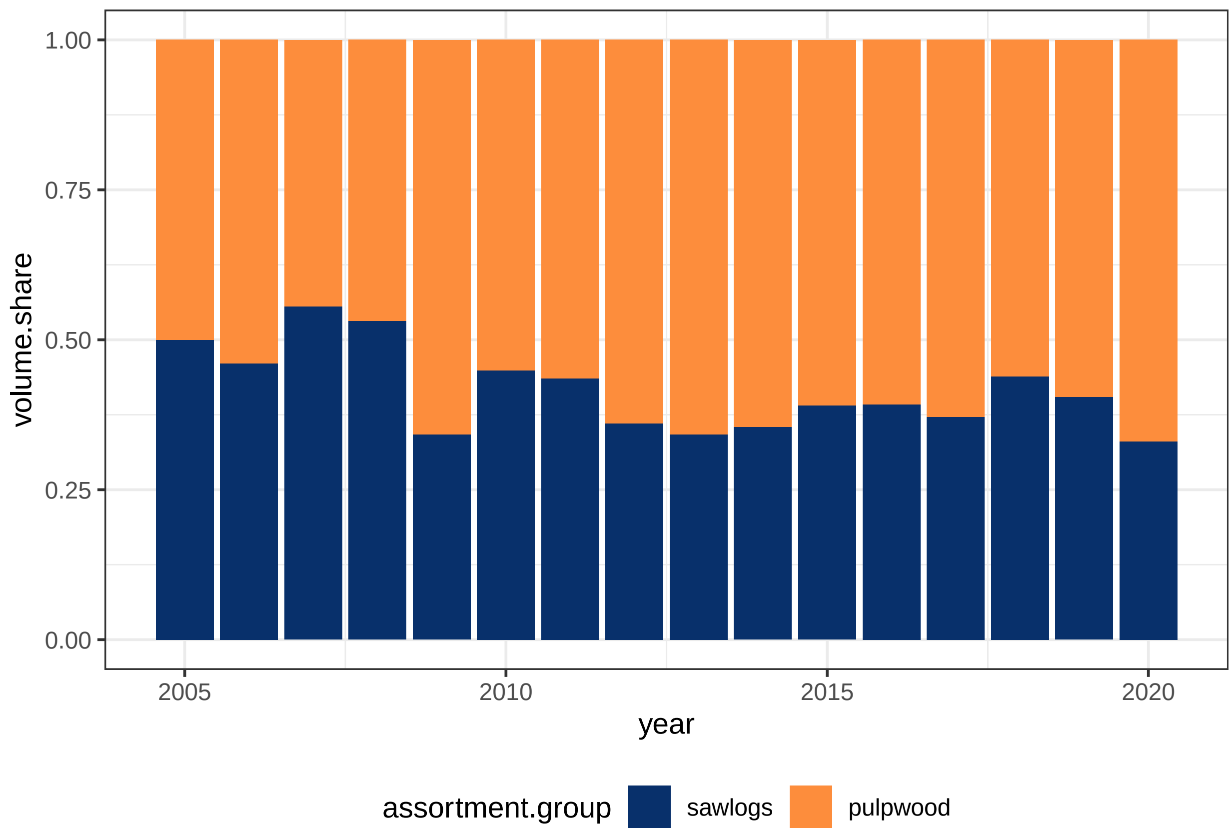

Figure 6: Time series of relative shares of sawlog and pulpwood assortments sold.

Supplement C: Suggested coefficients for bioeconomic simulation models. Supplementary Material to 'Quantifying the consequences of disturbances on wood revenues with Impulse Response Functions'.

Calculation framework for factors quantifying the consequences of disturbances on wood revenues

Using the simulated IRFs, irrespective of the models' quality, confidence bands, or our interpretations

		IRF - harvest.volume					IRF - share.wood.damaged					dummy	multipliers / shock intensities			summands			factor
		0	1	2	3	4	0	1	2	3	4		volume	damage	dummy	volume	damage	dummy	
spruce	stand	-0,121	-0,138	-0,095	-0,018	0,023						-0,202	0	1	0	0,00	0,00	0,00	0,00
	regional											-0,202	3,39	1	0	-0,24	0,00	0,00	-0,24
	national											-0,202	3,39	1	1	-0,24	0,00	-0,20	-0,44
beech	stand						0,006	-0,21	-0,303	-0,199	-0,021	0,003	0	1	0	0,00	-0,15	0,00	-0,15
	regional											0,003	0,19	1	0	0,00	-0,15	0,00	-0,15
	national											0,003	0,19	1	1	0,00	-0,15	0,00	-0,14

Using the simulated IRFs, but applying the suggested assumptions (yellow)

		IRF - harvest.volume					IRF - share.wood.damaged					dummy	multipliers / shock intensities			summands			factor
		0	1	2	3	4	0	1	2	3	4		volume	damage	dummy	volume	damage	dummy	
spruce	stand	-0,121	-0,138	-0,095	-0,018	0,023	-0,1	-0,1	-0,1	-0,1	-0,1	-0,202	0	1	0	0,00	-0,10	0,00	-0,10
	regional											-0,202	3,39	1	0	-0,24	-0,10	0,00	-0,34
	national											-0,202	3,39	1	1	-0,24	-0,10	-0,20	-0,54
beech	stand	-0,15	-0,15	-0,15	-0,15	-0,15	0,006	-0,21	-0,303	-0,199	-0,021	0	0	1	0	0,00	-0,15	0,00	-0,15
	regional											0	1	1	0	-0,15	-0,15	0,00	-0,30
	national											0	1	1	1	-0,15	-0,15	0,00	-0,30

Supplement D

species	year	calamity	harvest.vol	e.wood.damaged	revenues
beech	2005	0	0,885637104	0,0641252	0,720547166
beech	2006	0	1,172266514	0,06388973	0,76031622
beech	2007	1	1,242703881	0,449283133	0,97779139
beech	2008	0	1,061345263	0,203051401	1,098589288
beech	2009	0	0,614830494	0,072261594	0,93693171
beech	2010	0	0,823262975	0,22039522	0,948099061
beech	2011	0	1,115252767	0,097813806	1,043726936
beech	2012	0	1,056904968	0,051711223	1,040039917
beech	2013	0	1	0,09180789	1
beech	2014	0	1,039013859	0,063811224	1,047789903
beech	2015	0	1,088393441	0,085967518	1,073660976
beech	2016	0	0,882236253	0,052247982	1,063307423
beech	2017	0	0,793271722	0,066847471	1,008632794
beech	2018	0	0,859563404	0,193437258	1,059495555
beech	2019	1	0,653081389	0,216788119	1,049151965
beech	2020	1	0,464282928	0,472395349	0,9720121
spruce	2005	0	1,580182336	0,380019528	0,591728743
spruce	2006	0	1,64646482	0,555607458	0,685952091
spruce	2007	1	4,540829061	0,978523981	0,714441447
spruce	2008	0	2,352731766	0,950235191	0,713678563
spruce	2009	0	1,083731401	0,655547031	0,711610818
spruce	2010	0	1,817133479	0,826102671	0,870205716
spruce	2011	0	1,169704562	0,423011829	1,031830017
spruce	2012	0	0,962091312	0,266381175	1,016466073
spruce	2013	0	1	0,227608133	1
spruce	2014	0	0,998408771	0,200856571	1,054738753
spruce	2015	0	1,067620988	0,5238018	1,019410973
spruce	2016	0	1,089079178	0,190313917	0,967359067
spruce	2017	0	1,027122653	0,278702916	0,968262143
spruce	2018	0	2,797158876	0,949269332	0,78732467
spruce	2019	1	4,328891413	0,991491884	0,53179015
spruce	2020	1	4,333972758	0,962738802	0,323653929