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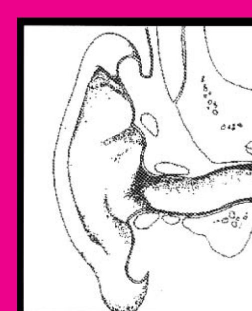

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Determining the direction of causality between psychological factors and aircraft noise annoyance

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Abstract

In this paper, an attempt is made to establish the direction of causality between a range of psychological factors and aircraft noise annoyance. For this purpose, a panel model was estimated within a structural equation modeling approach. Data were gathered from two surveys conducted in April 2006 and April 2008, respectively, among the same residents living within the 45 Level day-evening-night contour of Amsterdam Airport Schiphol, the largest airport in the Netherlands (n=250). A surprising result is that none of the paths from the psychological factors to aircraft noise annoyance were found to be significant. Yet 2 effects were significant the other way around: (1) from 'aircraft noise annoyance' to 'concern about the negative health effects of noise' and (2) from 'aircraft noise annoyance' to 'belief that noise can be prevented.' Hence aircraft noise annoyance measured at time 1 contained information that can effectively explain changes in these 2 variables at time 2, while controlling for their previous values. Secondary results show that (1) aircraft noise annoyance is very stable through time and (2) that changes in aircraft noise annoyance and the identified psychological factors are correlated.

Keywords: Aircraft noise annoyance, causal predominance, panel model, social-psychological factors

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Introduction

The degree of human response to aircraft noise is not only a function of acoustic variables but also of certain non-acoustic variables. Insight in these variables is important in order to predict noise annoyance reactions better[1] and also to deal with the problem of aircraft noise more effectively.[2,3] Although demographic characteristics significantly affect human reaction to noise,[4] research has shown that the most influential variables are social-psychological in nature, compromising attitudes towards the source, future expectations and feelings of control.[5,6] Yet evidence in support of these subjective (social-psychological) factors is largely based on cross-sectional survey data.[7] Since the independent and dependent variables are measured at the same time, the criterion of time precedence (i.e., X precedes Y in time) cannot be empirically investigated. In turn, this means that the direction of causation remains uncertain. In other words, the question remains whether the investigated social-psychological factors cause aircraft noise annoyance or vice versa.

The criterion of time precedence can be controlled under experimental conditions. Experiments allow the researcher to control which subjects are exposed to which treatment. For example, Glaser and Singer[8] have shown via several experiments that an individual's level of perceived control over the degree of noise exposure influences a person's noise reaction. In similar fashion, Maris *et al.*[9,10] have shown that the fairness of the procedures preceding the actual exposure to noise influences the degree of reported noise annoyance. Although these studies can firmly establish causality for the sample under investigation, the results cannot easily be generalized towards a population living around an airport. Specific sample characteristics, as well as the artificial laboratory settings, may hamper such generalizations.

A way to achieve both high external validity (can the results be generalized to other populations, times and places?) and high internal validity (does the cause X indeed lead to the effect Y?) is to combine the field survey with a certain experimental manipulation, resulting in what can be called a natural experiment. In such a situation, the manipulation is not directly under control by the researcher, but the occasion and the participants are chosen such that respondents can be categorized into a control group and a treatment group. The study by Hatfield *et al.*[11] is illustrative. Their study was conducted at Sydney airport, where, due to a runway configuration, aircraft noise levels in nearby areas were expected to increase, decrease or remain the same. In a survey before the actual change, Hatfield *et al.* found that expectations regarding future noise levels influenced people's psychological and physiological reactions to the noise. Given the methodological design, this result is both internally and externally valid. Of course, suitable occasions have to present themselves to assess the influence of possible other psychological determinants.

In this paper, we also aim to address the issue of causality. Specifically, we aim to establish the direction of causality between 12 (subjective) social-psychological factors, which are identified based on previous research[6] and noise reaction (i.e., noise annoyance). However, we take a somewhat different approach than the approaches described in the previous paragraphs. In contrast to these methods, we did not apply any manipulation. Instead, we estimated a structural equation model (SEM) based on panel data gathered from the field (i.e., data resulting from repeated measurements from the same individuals). A panel model can provide empirical tests for the time precedence criterion and hence address the issue of temporal order.[12-14] Via this methodological approach, we hope to retain both the advantage of a field study in terms of high external validity and the advantage of an experiment in terms of high internal validity.

Materials and Methods

A SEM panel model

Association, isolation (the exclusion of 'third variables') and direction of influence (temporal order) are generally viewed as the 3 requirements to establish a causal relationship.[15] An experiment in which the independent variable can be manipulated is a great aid in satisfying these requirements. However, it does not support a one-to-one generalization towards the field. On the other hand, cross-sectional field studies are only able to satisfy the criterion of association and to some extent of isolation (by statistical control of possible 'third variables'). The issue of temporal order can only theoretically be addressed. For example, if, in a cross-sectional study, a covariation is observed between age and the degree of noise annoyance, it is evident that the structural variable age causes noise annoyance and not the other way around. However, if the relation between a certain attitude and noise annoyance is examined, which are both subjective in nature, it becomes difficult to theoretically distinguish cause and effect.

To address the issue of temporal order within the field context and with subjective factors as independent and dependent variables, panel data can be used. Panel data contain measures of the same variables from numerous units observed repeatedly through time. The basic idea behind the specification of a model based on panel data is to estimate the effect of an independent variable X_{T1} (read 'X measured at time T1') on a second variable Y_{T2}, while controlling for Y's prior values (Y_{T1}). If X_{T1} is able to explain variation in Y_{T2} over and above the variation explained by Y itself at a previous point in time (Y_{T1}), it can be concluded that X_{T1} accounts for some change in Y_{T2} and hence that X is indeed a causal predictor of Y. A panel design is therefore effective in determining the temporal order between variables.

In sum, whereas models based on cross-sectional data can only satisfy the criteria of association (covariation) and nonspuriousness, a panel model can also *empirically* test the condition of time precedence. As such, it allows the researcher to investigate the 3 necessary conditions to establish a causal relationship. It needs to be noted, however, that although panel data offer ways to strengthen the causal inference process, they are not a cure-all for all the problems of causal inference in nonexperimental research.[13] Panel models still depend on (untestable) assumptions that have to be justified given the specific situations.

If the researcher has no prior conceptions about the temporal order between variables, the most appropriate model to test is a cross-lagged panel model. In this model, the dependent variables at time 2 are predicted by their previous values as well as the time 1 values of the other variable of interest. An example of a 2-wave cross-lagged panel model is depicted in Figure 1. The term 'cross-lagged' refers to the 2 lagged effects which cross each other in the middle.

In this model, parameters P1 and P2 represent the stability coefficients. These values can be interpreted as test-retest correlations, with values closer to 1 indicating higher relative stabilities. The remaining unexplained variation in X and Y at time point T2 can be regarded as variance resulting from individual changes which have occurred in the period between the two measurements. Assuming that the model is corrected for measurement errors in the observed variables.

Correlations C1 and C2 account for unmeasured variables

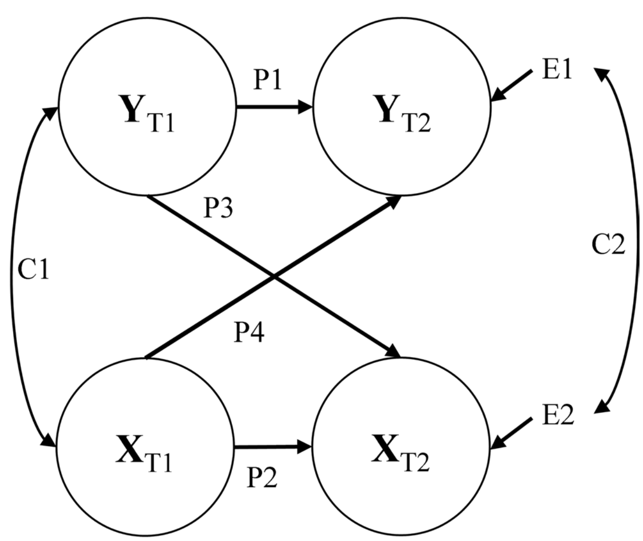

Figure 1: Specification of a two-wave cross-lagged panel model

and/ or unmodeled effects. Correlation C1 controls for the initial overlap between the exogenous variables X_{T1} and Y_{T1}, correcting for (1) previous causal influences between both variables and/ or (2) the effects of possible third variables. The error terms E1 and E2 indicate the variability in the endogenous variables X_{T2} and Y_{T2}, which is associated with unknown (unmodeled) factors. As a result, the correlation C2 accounts for (1) possible third variables that have influenced both X and Y within the period between the two measurements and (2) possible synchronous effects between X and Y. A synchronous effect should be understood as a change in Y at the second occasion (T2) resulting from a change in X at some time after the first occasion (T1).

While controlling for the initial overlap (C1) as well as for the influences of third variables and synchronous causal influences during the period between the two surveys (C2), the cross-lagged parameters P3 and P4 attempt to explain variance in X_{T2} and Y_{T2} which is not already explained by their respective stability coefficients (P1 and P2). The significance and strength of the parameters P3 and P4 inform us which of the two variables, X or Y, is the strongest temporal predictor.

Model specification and comparison

In addition to the reaction variable, aircraft noise annoyance, 13 social-psychological factors are taken into account (see also section 2.4, 'measures'). These factors are identified based on a previous literature study and a related empirical analysis.[6] Twelve of these are subjective in nature; while 1, the level of aircraft noise exposure, is objective. The 14 variables are combined into a 2-wave cross-lagged panel design as specified in Figure 2.

To investigate the different explanations for the observed covariance structure, 5 nested models are tested. First, we estimate a baseline model. This model consists of the 14 stability parameters, one for each of the included factors; and 91 correlations between the exogenous factors at time 1 [{N*(N-1)}/2 with N=14] (depicted on the left side in Figure 2).

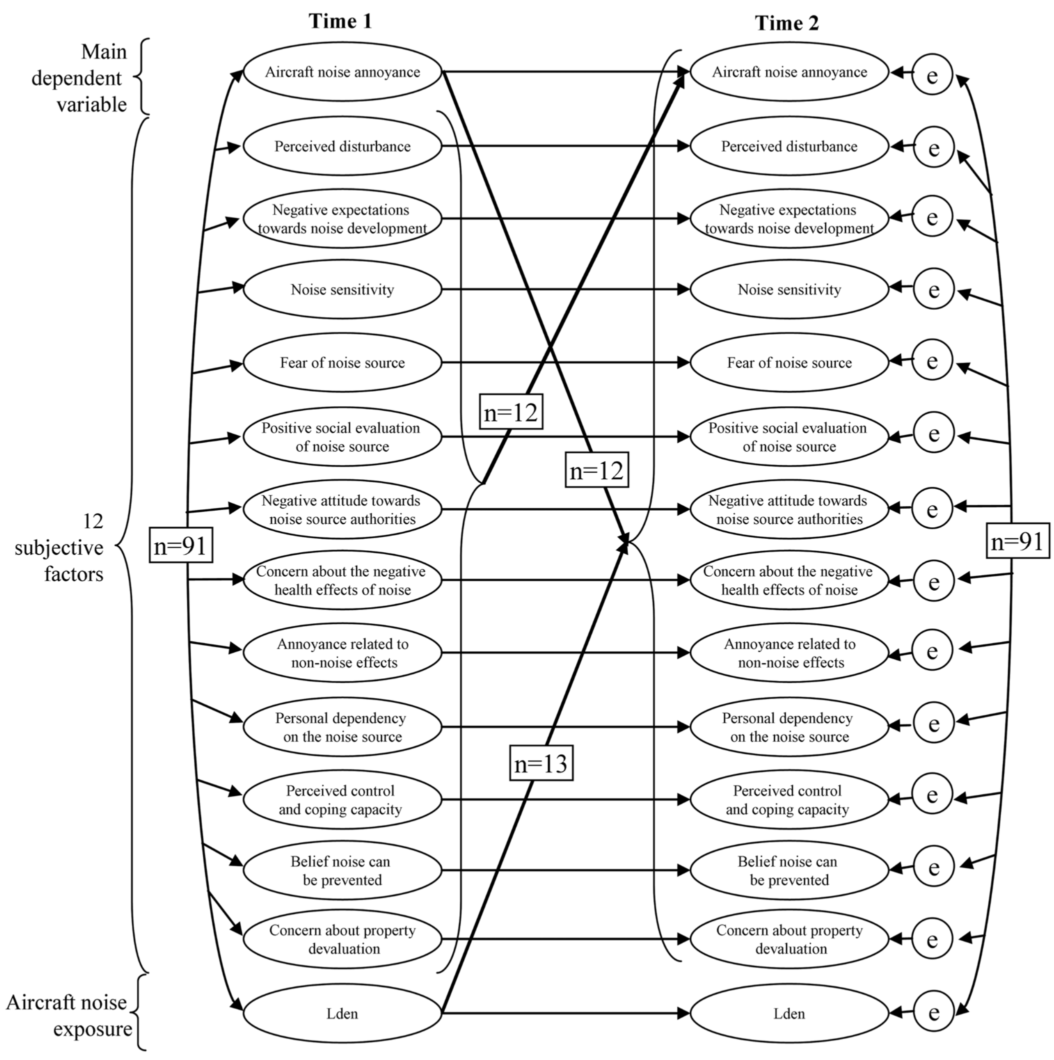

Figure 2: Model specification

In the second model, we also include the 91 correlations between the error terms of endogenous variables at time 2 (depicted on the right side in Figure 2). This model can provide insight into the extent to which the changes in the variables are correlated. These correlations are necessary to control for the influences of third variables and the presence of synchronous causal relationships between the model variables during the period between the two surveys.

In the third model, we estimate the 13 lagged effects of the level of aircraft noise exposure (L_{den}) on the endogenous variables, i.e., aircraft noise annoyance and the 12 psychological factors. (To keep the model clear, the arrows are taken together.) The reason for the inclusion of the aircraft noise exposure level is that it is a plausible 'third variable' which can underlie changes in the subjective variables (aircraft noise annoyance and the psychological factors). For example, a change in both 'aircraft noise annoyance' and 'attitude towards the noise source' might be due to a change in aircraft noise exposure. Inclusion of aircraft noise exposure is necessary to correct the lagged effects between these two variables for its influence. Hence the 13 lagged effects of aircraft noise exposure on the endogenous variables correct the estimations of the lagged effects between the 12 psychological factors and aircraft noise annoyance.

In the fourth and fifth model, we estimate the 12 paths from the psychological factors to aircraft noise annoyance and the 12 paths from aircraft noise annoyance to the psychological factors, respectively. Examination of the significance and strengths of these parameters can inform us whether the psychological factors or aircraft noise annoyance is/ are the predominant causal predictor(s), or whether perhaps reciprocal relationships exist. Our prime hypothesis is that the identified psychological factors influence aircraft noise annoyance. However, since there is little theory to support the hypothesis that the causal direction indeed flows from the identified factors to aircraft noise annoyance, the reverse hypothesis, i.e., aircraft noise annoyance influences the identified psychological variables, is also tested.

In line with the recommendations of Hu and Bentler,[16] the following fit indices are used to evaluate the models: the root mean square error of approximation (RMSEA),[17] which measures the discrepancy between the model implied and observed covariance matrix per degree of freedom; the standardized root mean residual (SRMR),[18] which measures the mean of the squared residuals (the differences between the sample and model-implied covariance matrices) divided by the standard deviations of the respective manifest variables; and the comparative fit index (CFI),[19] which provides a comparison between the specified model and a baseline model with zero constraints. A well-fitting model is defined as having values below 0.06 and 0.08 for RSMEA and SRMR, respectively, and a CFI value greater than 0.95.[16] In addition, to support model comparisons, we rely on chi-square difference tests, which can be performed for nested models.

Data-gathering procedures

The data were gathered in two surveys conducted in the periods April 2006 (time 1) and April 2008 (time 2). The details of the first survey (April 2006) are described in the study by Kroesen *et al.*[6] The main characteristics are reiterated here.

In all, 7000 residents living within the 45 L_{den} contour around Amsterdam Airport Schiphol were randomly sampled from the total population within this contour (approximately 1.5 million people aged 18 or above). Those sampled were invited via a letter to fill in an online questionnaire. With 646 useable responses, the response ratio was 9.2%. The mean sample age of 49.8 years deviated slightly from the mean population age of 46.7 years. Furthermore, residents with better education and a higher income were overrepresented. Such deviations can bias the results but also typical for postal or telephone surveys.[20] Hence they are generally difficult to avoid. At the end of the questionnaire, respondents could indicate whether they would be willing to participate in a second survey. In all, 505 people were willing and provided their e-mail address. These people were again approached 2 years later, in April 2008. A total of 269 people responded positively and filled in the exactly same questionnaire. Fifteen respondents were excluded from the analysis because their sex and age did not match between the two surveys. Twenty-three respondents indicated that they had moved in the period between the two surveys; however, 19 of them had moved to a location still within the 45 L_{den} contour around the airport. Three of the other 4 indicated that their reason to move was aircraft noise. The final response group consisted of 250 (= 269 − 15 − 4) useable responses. Hence the response rate for the second survey was 50.3%.

The panel data provided us with the opportunity to empirically assess the degree of nonresponse bias. In our particular case, it is plausible that people who are exposed to higher levels of aircraft noise or who are more annoyed by the noise are also more inclined to participate in a survey about the airport. The results indicated this was not the case. The mean L_{den} of nonrespondents in the second survey (n=236), 50.0 dB(A), did not differ significantly from the mean L_{den} of 50.1 dB(A) for those who did participate in the second survey (n=250). For the annoyance response, only the results of the first survey could be compared. The mean annoyance score in the first survey of those who were approached for the second survey but did not respond (n=236) was 4.2 [on a scale from 0 ('not at all annoyed') to 10 ('very much annoyed')], again not significantly different from the mean annoyance score of 4.1 for those who participated in the second survey also (n=250). Hence in April 2006, nonrespondents for the survey of April 2008 were equally annoyed by aircraft noise as respondents who participated in both surveys.

Ideally the time lag between measurements should be chosen such that it reflects the time it takes for the causal effect to evolve.[21] However, in most cases one can only guess how long that is. Given that in the present study we measured several attitudinal constructs, which are generally relatively stable through time, we assumed that a period of 2 years was long enough for changes in individual scores to occur, but not too long for too much nonresponse. Moreover, with a time lag of 2 whole years, the design controlled for the seasonal fluctuation in annoyance response, i.e., the empirical trend that in the summer noise reaction is slightly greater than in the winter.[22]

Measures

The main dependent variable, aircraft noise annoyance, and the 12 psychological factors were measured via multiple items to increase their reliability. The constructs are calculated through summation of the individual items. An overview of the construct labels, the number of items per construct, the construct means and standard deviations, and the construct reliabilities at both time points is provided in Table 1. Details on the individual items used can be found in the study by Kroesen *et al.*[6]

With one exception, the constructs showed acceptable construct reliability (Cronbach's alpha >0.70). Each construct was included in the structural model as a latent variable with a single observed indicator, which is represented by the summated scale. The reliability of each latent variable is taken into account by fixing the measurement error of the indicator variable at a value of {(1−Cronbach's alpha) multiplied by the variance of the respective summated scale}.[23] In this way, the parameters associated with the structural paths in the model are corrected for measurement errors, leading to less biased estimations.

In addition to the subjective constructs, the degree of aircraft noise exposure is included in the model and represented by the noise exposure metric L_{den} dB(A). For every respondent in the sample, the level of noise exposure (a year's mean level based on the 12-month period preceding the surveys) was calculated by the National Aerospace Laboratory (NLR), the Netherlands. This was done by transforming the 4-digit 2-letter postal code of each respondent's residence, which includes on an average an area of 50 m2 (approximately 15 households) into XY-coordinates, which are subsequently used to determine the level of noise exposure at the particular location.

Results

Four construct means differed significantly between the two measurements [Table 1]. The means of the variables 'negative expectation towards noise development,' 'fear of the noise source,' 'positive social evaluation of the noise source' and 'belief that noise can be prevented' decreased significantly. The mean of the variable 'perceived control and coping capacity' increased significantly. Overall, the deviations were minor, even the significant ones.

Five models were estimated using the standard maximum likelihood procedure. The software package AMOS 7 was used for this purpose. In Table 2, the fit indices of the models are presented.

The fit of the baseline model (M1) was found to be poor. The values of the RMSEA and CFI were outside the respective acceptable cut-off values (RMSEA >0.06 and CFI <0.95). Only the value of the SRMR lay within the acceptable range (SRMR <0.08).

Addition of the correlations between the error terms of the endogenous variables (the time 2 variables) was found to drastically improve the model fit. The three fit indices then showed an acceptable model fit, and the chi-square difference test showed that the improvement in model fit between model 1 and model 2 was indeed significant (M2 *vs.* M1: $\Delta\chi$=477.36; Δd.f., 91; *P*<.000). The large improvement in model fit can be taken as evidence for *either* the influence of unmeasured third variables *or* the presence of synchronous effects between the variables in the model. However, we cannot empirically assess which of the two explanations is (more) valid.

Addition of the paths from L_{den} at time 1 to the 13 endogenous variables at time 2, i.e., aircraft noise annoyance and the 12 psychological factors, also shows a significant improvement in model fit (M3 vs. M2: $\Delta\chi$=36.92; Δd.f. 13; *P*<.000). Looking at the (standardized) parameter estimates, the following paths are significant: $L_{den} \rightarrow$ concern about the negative health effects of noise (β=0.138; *P*=.000); and $L_{den} \rightarrow$ annoyance related to non-noise effects (β=0.128; *P*= .004). Hence changes that have occurred in these variables in the period between the two surveys can be explained by the level of aircraft noise exposure at time 1.

Model 4 introduces the lagged effects of the psychological factors on aircraft noise annoyance. With this addition, no improvement in model fit occurred. Hence we can conclude that variance in the psychological factors at T1 is unable to explain variance in aircraft noise annoyance at T2, controlling for the influence of aircraft noise annoyance at T1. In other words, the psychological factors at T1 contain no information through which we can determine how people's annoyance response had changed within the period between the two measurements.

The reverse hypothesis, i.e., aircraft noise annoyance influences the psychological factors, is supported by the data. The difference in the chi-square values of models 5 and 3, Δ36.92 (Δd.f. 12), was statistically significant (*P*= .000), again indicating an improvement in model fit. Hence aircraft noise annoyance at T1 can predict changes in the identified

Table 1: An overview of the constructs

n=250		Mean		Standard deviation		Cronbach's alpha		Δ T1-T2	
	# items	T1	T2	T1	T2	T1	T2	Mean	Sign.
Main dependent variable (summated scale)									
Aircraft noise annoyance (past 12 months)	2	6.2	6.0	3.5	3.5	0.92	0.91	-0.2	0.27
Determinant (summated scale)									
Perceived disturbance	5	12.7	12.8	4.9	4.8	0.88	0.89	0.1	0.63
Negative expectations towards noise development	2	10.1	9.7	2.6	2.6	0.83	0.82	-0.4	0.01
Noise sensitivity	8	26.6	25.9	8.1	8.3	0.86	0.87	-0.7	0.09
Fear of noise source	2	4.3	3.9	2.6	2.4	0.76	0.74	-0.4	0.00
Positive social evaluation of noise source	3	17.7	16.2	3.2	3.6	0.79	0.81	-1.5	0.00
Negative attitude towards noise source authorities	8	32.8	33.5	11.4	11.8	0.91	0.94	0.7	0.18
Concern about the negative health effects of noise and pollution	4	13.8	14.3	7.2	6.9	0.92	0.93	0.5	0.22
Annoyance related to non-noise effects	3	7.3	7.4	4.7	4.6	0.85	0.86	0.1	0.62
Personal dependency on the noise source	3	5.6	5.8	4.3	4.1	0.69	0.70	0.2	0.49
Perceived control and coping capacity	3	13.3	13.8	4.6	4.5	0.78	0.77	0.5	0.01
Belief that noise can be prevented	1	4.6	4.4	1.4	1.5	0.83	0.83	-0.2	0.03
Concern about property devaluation	1	1.9	2.1	2.0	2.0	0.83	0.83	0.2	0.27
Aircraft noise exposure									
L_{den} dB(A)	-	50.1	50.1	2.3	2.5	-	-	0.0	1.00

Table 2: Model evaluation and comparison

Model	Specification	RMSEA	SRMR	CFI	χ	df	P	Model comparison	Δχ	Δdf	P
M1	91 correlations between exogenous variables (T1) and 14 stability coefficients (baseline model)	0.084	0.060	0.91	751.60	273	0.000				
M2	M1 + 91 correlations between error terms of endogenous variables (T2)	0.045	0.045	0.98	274.24	182	0.000	M2 vs. M1	477.36	91	0.000
M3	M2 + 13 paths from Lden (T1) to endogenous variables (T2)	0.041	0.040	0.99	237.32	169	0.000	M3 vs. M2	36.92	13	0.000
M4	M3 +12 paths from psychological factors (T1) to aircraft noise annoyance (T2)	0.042	0.040	0.99	225.07	157	0.000	M4 vs. M3	12.25	12	0.426
M5	M3 +12 paths from aircraft noise annoyance (T1) to psychological factors (T2)	0.034	0.027	0.99	201.02	157	0.006	M5 vs. M3	36.30	12	0.000

RMSEA: root mean square error of approximation, SRMR: standardized root mean residual, CFI: comparative fit index

factors at T2, while controlling for the factors' previous values. Examination of the parameter estimates shows that 2 paths are significant: (1) aircraft noise annoyance → concern about the negative health effects of noise (β=0.181; *P*= .002) and (2) aircraft noise annoyance → belief that noise can be prevented (β=0.298; *P*= .000). Changes in these variables are predicted by aircraft noise annoyance at T1.

Given the objective of the present paper, the results are contrary to expectations. We were not able to reveal any significant effects from the psychological factors to aircraft noise annoyance. Moreover, only 2 effects were significant the other way around. Yet we can offer two explanations for the present results, which are intrinsically relevant in light of our aim. The empirical evidence for these explanations is provided in Table 3, which presents the 91 correlations between the time 1 exogenous variables and the 14 stability coefficients (on the diagonal).

The first explanation relates to the correlations between the time 1 exogenous variables. It can be observed that the intercorrelations between the constructs are generally high. The strong overlap between the exogenous variables has a suppressive effect on the estimated cross-lagged relationships. Hence, given that several 'time 1' variables are (empirically) indistinctive, they have no explanatory force over and above the autoregressive effects (i.e., the stability coefficients).

The second explanation relates to the stability coefficients. These coefficients are generally high, ranging from 0.58 (for 'belief that noise can be prevented') to 0.92 (for 'personal dependency on the noise source'), indicating that the psychological variables are very stable. In other words, little individual changes had occurred in the period between the two surveys. Given that the unexplained proportions of variance in the endogenous variables were small, there remained little variance to be predicted by the time 1 exogenous variables, which, in turn, decreased the probability of any cross-lagged effect to become significant.

Hence due to the consistency of variable scores at one moment in time, as well as the consistency of variable scores over time, any lagged effect has to be very strong to overcome these two 'suppressors.' Model 5 showed that only 2 lagged effects were indeed strong enough to become significant. Although the presence of lagged effects can be largely excluded, the substantial increase in model fit between models 1 and 2 (with the addition of correlations between the error terms of the endogenous variables) indicates that changes in the model variables *are* correlated. Table 4 presents the correlations between the error terms of the endogenous variables. Here, a significant correlation between 2 residual terms indicates that the changes in the 2 respective variables are correlated. From this table, it can be deduced that change in aircraft noise annoyance is significantly associated with changes in the other variables. These parallel changes cannot be explained by the cross-lagged relationships.

Discussion

Although the presence of lagged effects can be (largely) excluded, the substantial correlations between the error terms of the endogenous variables [Table 4] indicate that the model variables did change in the same directions. Two explanations can account for this empirical trend. One is that unmeasured third variables had influenced the model variables during the period between the two surveys; the other is that (unidirectional or reciprocal) synchronous effects between the variables exist.

Related to the first explanation ('third variable' influence), we can speculate that (1) a psychological explanation, (2) a social explanation and/ or (3) an acoustical explanation can account for the correlated changes. Related to the psychological explanation, it might be that a personal factor like 'negative affectivity,' a general tendency to have a negative view of oneself and the environment,[24] is responsible for the changes in pairs of variables. The permanent exposure to noise may eventually bring people into a negative affective state.[25]

Alternatively, it might be that some sort of socialization process underlies the correlated changes. Bröer[26] and Kroesen and Bröer [27] recently showed the relevance of this explanation. These authors assumed that policy actors' conceptualization of the noise problem would resonate among the general public and would shape the necessary evaluative frames to feel annoyed. Since these frames were defined as sets of interrelated positions, this explanation fits nicely with the observed correlational pattern in Table 4, which shows that many changes among the variables are correlated. In other words, the interrelated changes are congruent with the idea of a frame, which, if a shift occurs, would result in a change in a whole set of different variables.

An acoustical explanation can also not wholly be ruled out. In the model, all effects between exogenous and endogenous variables are controlled for the level of aircraft noise exposure in L_{den} at time 1 (model 3). In addition, given that this variable has a stability coefficient of 0.98 [Table 3], very few changes occurred in this variable between the two surveys. Yet, although L_{den} cannot be responsible, it might be that changes occurred in the structure of the noise load. In this respect, Guski[28] mentions the empirical trend that the average noise load of single events generally decreases, but that the number of events increases. Such a change would be concealed by an annual energy-equivalent noise metric like L_{den} and can also provide a plausible 'third-variable' explanation.

Finally, it should be noted that the psychological, social and acoustical explanations do not cancel each other out and may be empirically interwoven in many ways.

The second explanation for the correlated error terms is that synchronous effects between the variables exist, which would imply that changes in the variables *after* the first measurement at time 1 led to the changes in the endogenous variables at the second measurement.[12] In our model, such synchronous effects would also be captured by the correlations between the error terms of the endogenous variables.

Again, however, we cannot empirically assess the validity of these competing explanations (i.e., the influence of 'third variables' versus that of synchronous effects). The only conclusion we can draw that is relevant in light of our aim is that the values of many variables in the model had changed in similar directions.

In all, we can conclude that establishing the direction of causality between aircraft noise annoyance and psychological variables in the field remains a difficult project. As the present study has illustrated, this conclusion holds even when panel data are available. Although providing direct (internally and externally valid) evidence remains difficult, it should be noted that the lack of explanatory power of acoustic variables in relation to individual subjective noise reactions can be taken as indirect evidence that these social-psychological variables do indeed matter.

Conclusion

In this paper, we aimed to establish the direction of causality between several psychological factors and aircraft noise

Table 3: Correlations between exogenous variables (in the lower left triangle) and stability coefficients (on the diagonal)

Construct	NA	PD	NE	NS	FN	PS	AS	CH	NN	DS	CC	BP	DV	L_{den}
Noise annoyance (NA)	.80													
Perceived disturbance (PD)	.92	.86												
Negative expectations towards noise development (NE)	.68	.66	.62											
Noise sensitivity (NS)	.52	.52	.42	.91										
Fear of noise source (FN)	.61	.60	.52	.44	.82									
Positive social evaluation of noise source (PS)	-.53	-.48	-.57	-.45	-.54	.82								
Negative attitude towards noise source authorities (AS)	.65	.59	.74	.50	.54	-.84	.84							
Concern about the negative health effects of noise and pollution (CH)	.80	.79	.70	.57	.67	-.63	.74	.87						
Annoyance related to non-noise effects (NN)	.64	.62	.49	.43	.62	-.56	.59	.78	.90					
Personal dependency on the noise source (DS)	-.18	-.21	-.38	-.13	-.12	.27	-.39	-.26	-.08	.92				
Perceived control and coping capacity (CC)	-.78	-.73	-.71	-.57	-.54	.55	-.74	-.83	-.61	.28	.91			
Belief that noise can be prevented (BP)	.52	.50	.59	.32	.46	-.61	.68	.59	.45	-.23	-.59	.58		
Concern about property devaluation (DV)	.46	.44	.43	.27	.39	-.29	.45	.48	.41	-.09	-.42	.40	.80	
Aircraft noise exposure (L_{den})	.17	.19	.13	.17	.06	-.15	.26	.17	.24	-.07	-.16	.09	.17	.98

Underlined: significant at $P< .05$

Table 4: Correlations between the error terms of the endogenous variables

Construct	NA	PD	NE	NS	FN	PS	AS	CH	NN	DS	CC	BP	DV
Noise annoyance (NA)													
Perceived disturbance (PD)	.95												
Negative expectations towards noise development (NE)	.45	.46											
Noise sensitivity (NS)	.31	.16	.22										
Fear of noise source (FN)	.25	.24	.22	.21									
Positive social evaluation of noise source (PS)	-.07	-.14	-.05	-.07	-.11								
Negative attitude towards noise source authorities (AS)	.28	.22	.53	.11	.01	-.49							
Concern about the negative health effects of noise and pollution (CH)	.53	.54	.34	.48	.17	-.30	.37						
Annoyance related to non-noise effects (NN)	.21	.27	.21	.66	.35	-.09	.18	.29					
Personal dependency on the noise source (DS)	-.07	.05	-.12	-.29	-.02	.30	-.18	-.17	-.14				
Perceived control and coping capacity (CC)	-.77	-.77	-.48	-.38	-.10	.63	-.65	-.72	-.32	-.05			
Belief that noise can be prevented (BP)	.24	.22	.35	.29	.28	-.34	.44	.19	.35	-.32	-.19		
Concern about property devaluation (DV)	.23	.22	.36	.07	.30	-.51	.29	.47	.44	-.19	-.44	.19	
Aircraft noise exposure (L_{den})	-.08	-.11	-.02	-.02	.02	.16	-.09	.07	.06	.07	.24	-.05	-.08

Underlined: significant at $P< .05$

annoyance. For this purpose, a panel model was estimated within a structural equation modeling approach. Data were gathered at two moments in time from the population living within the 45 L_{den} contour around Schiphol airport. Preliminary analysis of the data showed that there was no nonresponse bias with respect to aircraft noise exposure and aircraft noise annoyance. The results of the main analysis indicate that none of the paths from the psychological factors to aircraft noise annoyance are significant. Yet 2 effects were found to be significant the other way around: (1) from 'aircraft noise annoyance' to 'concern about the negative health effects of noise' and (2) from 'aircraft noise annoyance' to 'belief that noise can be prevented.' Hence aircraft noise annoyance measured at time 1 contained information that can effectively explain changes in these 2 variables at time 2, while controlling for their previous values. In sum, our main hypothesis, i.e., the identified psychological factors influence aircraft noise annoyance, could not be confirmed. Secondary results show that (1) aircraft noise annoyance is very stable through time (stability coefficient of 0.83) and (2) that changes in aircraft noise annoyance and the identified psychological factors are correlated.

Establishing the direction of causality between aircraft noise annoyance and possible social-psychological factors is important for noise policy. Policies specifically aimed at these factors can only be effective if the causality indeed 'flows' from these factors to aircraft noise annoyance. A second and related issue, which is also relevant for policy, is whether individual differences can be attributed to social or psychological variables and processes. If, for instance, personality traits appear to be dominant in the explanation of individual differences, more individually 'tailored' noise policies would be preferable. If, on the other hand, social representations are dominant in structuring noise perception and evaluation, a closer examination of the collective noise policy and the message it brings across would be more appropriate.

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