FDZ

Research Data Centre (FDZ)
of the German Federal
Employment Agency (BA)
at the Institute for
Employment Research (IAB)

FDZ·Methodenreport

04/2010
EN

Methodological aspects of labour market data

The Impact of Cleansing Procedures for Overlaps on Estimation Results – Evidence for German Administrative Data

Patrycja Scioch

Bundesagentur für Arbeit

The Impact of Cleansing Procedures for Overlaps on Estimation Results – Evidence for German Administrative Data

Patrycja Scioch (Institute for Employment Research)

Die FDZ-Methodenreporte befassen sich mit den methodischen Aspekten der Daten des FDZ und helfen somit Nutzerinnen und Nutzern bei der Analyse der Daten. Nutzerinnen und Nutzer können hierzu in dieser Reihe zitationsfähig publizieren und stellen sich der öffentlichen Diskussion.

FDZ-Methodenreporte (FDZ method reports) deal with the methodical aspects of FDZ data and thus help users in the analysis of data. In addition, through this series users can publicise their results in a manner which is citable thus presenting them for public discussion.

Contents

Abstract

Process-generated and administrative datasets have become increasingly important for labor market research over the past ten years. Major advantages of these data are large sample sizes as well as absence of retrospective gaps and unit non-responses. Nevertheless, the quality and validity of the information remains unclear and a lot of preparation and data cleansing is necessary before the data are analyzable. Unfortunately, only few researchers provide access to their cleansing procedures and therefore, also the impact of them on the results of the analyses is unidentified. This paper contributes to this subject and focuses on the variation of research results due to alternative data cleansing procedures. In particular, the paper uses the framework for data preparation suggested in an evaluation study by Wunsch and Lechner (2008) as a benchmark and then induces variation by developing different cleansing procedures for overlapping and parallel observations. The descriptive results show that the differences between the data sets (based on the different procedures) show various magnitudes on some attributes concerning time and personal characteristics. Similar results appear for the subsequent analysis of the treatment effects, which do not vary in the overall shape but in the magnitude especially during the lock-in effect. In sum the results of the analysis indicate that the empirical findings of the evaluation method are fairly robust to variations in the underlying cleansing procedure.

Zusammenfassung

Prozessgenerierte und administrative Datensätze sind in den vergangenen 10 Jahren für die Arbeitsmarktforschung zunehmend wichtiger geworden. Bedeutende Vorteile dieser Daten sind einerseits große Stichprobenumfänge sowie andererseits das Fehlen von Erinnerungslücken und Unit Non-Responses. Dennoch bleibt die Qualität und Validität der Informationen weiterhin unklar, so dass zahlreiche Bereinigungen und Datenaufbereitungen notwendig sind bevor die Datenanalyse möglich ist. Leider stellen nur wenige Wissenschaftler ihre Datenbereinigungsverfahren zur Verfügung, womit auch deren Einfluss auf die Analyseergebnisse unbekannt ist. Diese Studie konzentriert sich auf die Abweichungen von Forschungsergebnissen aufgrund von alternativen Datenbereinigungsverfahren. Speziell wird eine in Wunsch und Lechner (2008) angewendete Methode als Maßstab verwendet und Variation durch die Entwicklung verschiedener Datenbereinigungsverfahren für sich überschneidende und parallele Beobachtungen erzeugt. Die deskriptiven Ergebnisse zeigen, dass die Differenzen zwischen den Datensätzen (basierend auf den verschiedenen Verfahren) hinsichtlich einiger zeitlicher und personeller Charakteristika unterschiedliche Ausmaße aufweisen. Ähnliche Ergebnisse zeigen sich in den aufsetzenden Analysen der Treatment Effekte, die sich im allgemeinen Verlauf bis auf die Ausmaße nicht unterscheiden. Größere Abweichungen treten vor allem während dem lock-in Effekt auf. Zusammenfassend zeigen die Ergebnisse, dass die empirischen Befunde der Evaluationsmethode ziemlich robust gegenüber Abweichungen in den zu Grunde liegenden Datenbereinigungsverfahren sind

Keywords: administrative data, cleansing procedures, data quality

JEL-Classification: C81, J68

1 Indroduction

Process-generated and administrative datasets have become increasingly important in labor market research in Europe over the past ten years. While other countries like the USA used administrative data already earlier in the evaluation of training programs (Ashenfelter, 1978; Angrist 1998; Mueser et al. 2007) or for statistical uses (Jabine and Scheuren, 1985) the development in Europe was rather slow. Kluve et al. (2006), for example, reports that in the late 1990's most countries used survey data for labor market policy evaluation. He adds that over the past decade this changed and now the vast majority (almost 75%) of microeconomic evaluation studies in Europe are based on administrative data. Particularly Scandinavian labor market research shows that register data can be a valuable source for empirical research (for example Eliason and Storrie 2006; Carling and Richardson 2004; Roed and Raaum 2003; Geerdsen and Holm 2004; Hämäläinen and Ollikanen 2004).

In Germany since 2000 the number of studies increased due to efforts of different research groups from various institutes who were trying to utilize administrative data from the Federal Employment Office (Klose and Bender 2000; Hujer et al. 2004; Lechner et al. 2004; Fitzenberger and Speckesser 2007). Another cornerstone was the official expertise of the Committee for the Improvement of the Informational infrastructure between Sciences and Statistics (in German: Kommission zur Verbesserung der informationellen Infrastruktur zwischen Wissenschaft und Statistik; KVI 2001) which recommended the construction of Research Data Centers (RDC) and Data Service Centers (DSC). These were first established in 2004 to provide access to administrative data for research (e.g. the RDC of the Federal Employment Agency in the Institute for Employment Research). This new service resulted in a growing number of research based on this type of data (for example Lechner and Miquel 2009; Bauer et al. 2007; Rinne et al. 2008; Fitzenberger et al. 2009).

In comparison to traditional survey data register data have much larger coverage of observations. Especially, administrative data are for instance used to overcome weaknesses of survey data like attrition bias, reporting or collection bias, the lack of relevant comparison groups and small sample size. However, the most important advantage of administrative data concerns the option of merging information from different sources and over multiple points of time.

Nevertheless, up to now there are only a few studies that focus on the quality and usability of administrative data. In contrast this topic is widely used in reference to survey data and has been the subject of research for 20 years (e.g. Groves 2004; Groves et al. 2004). If focusing on administrative data quality research is mainly focused on assessing the quality and the representativeness of survey data (see e.g. Pyy-Martikainen and Rendtel 2008; Reimer and Künster 2004; Jenkins et al. 2005; van den Berg et al. 2004) or to find out if there is a difference between using register and survey data and if therefore one source can be declared as the "better" one (see e.g. Blank et al. 2009; Rendtel et al. 2004; Hotz and Scholz 2001).

With regard to the quality and usability of process generated data the literature about identifying, measuring and improving data quality is scant in almost all countries. Jabine and

Scheuren (1985) defined some goals for statistical uses of administrative records and Wallgren and Wallgren (2007) describe the use for statistical purposes. But besides quality issues when producing statistics this topic is not or only scarcely subject of evaluation analyses, neither as a point of their own, nor as part of evaluation studies. Johansson and Skedinger (2005) evaluate the misreporting of the disability status in the Public Employment Service in Sweden and Rendtel et al. (2004) analyze the reliability of Finish income data. For Germany Fitzenberger et al. (2006) develop imputation rules to improve the education variable in a widely used administrative data set and some analyses concentrate on the data generating process and its complexity (e.g. Kruppe and Oertel 2003; Engelhardt et al. 2008). Further studies show that using administrative data there are, similar to surveys, problems like missing values, overlaps and inconsistencies. Jaenichen et al. (2005) and Bernhard et al. (2006) for example identify distinctive types of implausible cases in a German data set and discuss simple heuristics to handle these types of inconsistencies. They focus on overlaps and gaps and refer to the requirement of data preparation and data cleansing. More recent work like Kruppe et al. (2008), Fitzenberger and Wilke (2009) and Waller (2008) also focuses on the link between research results and data cleansing procedures. The first two studies deal with the different definitions of unemployment and possible effects on evaluation results while the latter develops different correction procedures for the end dates in program participation and discusses the influence on estimation results. She finds only little differences in the treatment effects caused by the measurement errors.

Due to the possibility of merging data from different sources and the fact that administrative data are not directly collected by the researcher almost every study which uses administrative data is cleansing the data before applying the analysis of interest. Unfortunately data cleansing procedures are seldom described in sufficient manner which therefore not allows a satisfying reconstruction of the analysis set up. Likewise, sensitivity analyses are also seldom conducted which would emphasize the potential impact of the data cleansing procedures on the results of the analysis.

This study contributes to the latter type of problem. By the example of an evaluation study this paper investigates the impact on evaluation results of different cleansing procedures in a merged administrative dataset that is of substantial interest and widely used in labor market policy evaluation in Germany. Previous studies (e.g. Stephan 2008) showed that the meaning of estimated treatment effects and their size depend strongly on the choice of treatment and comparison group. Therefore this point is held stable during the investigation and the paper focuses on the cleansing of record overlaps and inconsistencies between the different sources of this database. In a first step the data cleansing approach suggested by Wunsch and Lechner (2008)[1] is reconstructed and the whole analysis of the training programs in Western Germany is conducted. In a second step variations of the cleansing procedure are developed and the effects of the variations on the point estimates within the evaluation framework are analyzed by confronting the results gained by each cleansing method with the results of the reference method. Similar to Waller (2008) there are no huge differences between the effects and the main differences occur in the short run in the so called lock-in ef-

[1] I thank Conny Wunsch and Michael Lechner for supporting the work related to this paper and for giving access to their programme codes.

fects. Therefore the results emphasize that the empirical findings seem to be robust to variations in the underlying cleansing procedure.

The discussion of the analysis is organized in 6 subsections, which are structured as follows: In the next section the database is described and problems are discussed that may occur when using this large administrative database with its richness of information and large sample size on the one side and its inconsistencies and overlapping records on the other side. Section 3 outlines the general framework and describes in detail the cleansing procedure suggested by Wunsch and Lechner (2008). I use this cleansing procedure as benchmark in all later sections to identify potential differences and discuss the later results. Section 4 describes the development of the new cleansing procedures before section 5 presents and discusses the descriptive statistics and point estimation results. Section 6 summarizes the main findings and concludes.

2 Database

The database used in this study is the Integrated Employment Biographies[2] (IEB) of the Institute for Employment Research (IAB) in Germany, which is a longitudinal dataset merged from four distinct process generated data sources. The data cover nearly 80% of the total labor force in Germany and almost 100% of the employees liable to social security. Not included are periods of self-employment, civil servants and periods of childcare leave. The data set's sources are filled by four administrative processes, and are linked by an unique identifier. Each of these sources offers a brought set of attributes and covers different periods of observation.

- The first data source is the *Employment Histories* containing employment periods captured by the social insurance register back until 1990. Besides begin and end dates of employments it also includes the employment status, personal characteristics like gender, education, experience, age and nationality, information about the employment like daily wage, occupational status, type of profession, region and the industry. Moreover it allows merging further information about the employer on an establishment identifier and an unequivocal attribution of records to individuals by an individual identifier. Changes in territorial allocation are updated in current observations as well as in previous ones.

- The second data source contains data on spells of unemployment from the *Benefit-Recipient-History*. It has information, on a daily basis, on the amount and duration of receipt of unemployment benefits, unemployment assistance and subsistence allowances since 1990. Additionally, the source includes personal characteristics and statements on sanctions due to absence of cooperation with the PES or non-appearance at interviews with the PES staff.

[2] Unfortunately there is no English data description but the structure and general content is the same as in the IEBS which is a weak anonymized 2% sample available at the Research Data Centre of the Federal Employment Agency in the IAB (see Jacobebbinghaus and Seth, 2007).

- Most of the individual characteristics in the IEB data arise from the *Applicants-Pool data*, which contains information on job-searching spells since 1999. Apart from the current marital state, nationality, health, education and regional characteristics the data set also comprises information about the last job, the desired job and profession.

- Finally the data set on *Active Labor Market Program* Participation provides information on periods spent in promoted schemes (e.g. training programs). Since 2000 any participation in employment, training or job-creation measures with begin and end date, personal characteristics of respective participants and information about the program, like contents and individual success has been recorded.

It is important to note that the sources are not cross-validated, which may cause the existence of parallel observations (overlaps). Individuals can have several jobs at the same time or they might be employed and searching for a new job or receiving benefits while on job search or participating in labor market programs. These spells can be completely parallel, one may embed the other or they are overlapping. The existence of parallel observations is twofold: It may offer additional information, like periods of promoted employment or it may also cause problems when information is contradictory. This can be the case, for example, if an individual is participating in a full-time training program and has a full-time employment observation parallel to this. In such a case one must decide which data source to believe and to chose - which is the subject of data cleansing procedures.

To combine the abundance of information technically in one manageable data set a variety of characteristics of each source has to be selected and linked. Köhler and Thomsen (2009) describe elaborately the data integration and consolidation while Seysen (2009) specifies the effects of changes in data collection mode on their quality. The IEB data are organized on a daily basis and allow therefore controlling for time varying covariates. Due to the huge size of the IEB a 2.2% random sample is used in this study enriched with additional information from the four sources and a wide range of regional statistics added from INKAR[3] like local unemployment rate, the share of foreigners, labor-force participation rate, household income or share of long-term unemployed. As described above the data are prone to parallel and overlapping observations. This is reflected in the increasing number of overlaps in the data. The 2.2% sample of the IEB has 34% overlapping observations in the period from 1990-2000. Afterwards this number increases up to 49%, which means that in almost half of the cases decisions have to be made which observation to chose.

3 Benchmark

The study refers to a meanwhile broad strand of research that is concerned with the evaluation of the outcome of labor market programs on the micro level (e.g. Lechner et al., 2004;

[3] Dataset of the Federal Institute for Research on Building, Urban Affairs and Spatial Development

Biewen et al., 2007; Mueser et al., 2007; Osikominu, A., 2008; Fitzenberger et al., 2009). Though, it is not in the focus to discuss the general underlying framework of evaluation methods but to use their underlying set up for the study of the effect of data cleansing procedures. In particular, I will refer to the study presented by Wunsch and Lechner (2008) to create a benchmark and allow for variance in the way of conducting the data cleansing. Their effect on the supplemented outcome measures will be investigated.

This choice was made for four reasons, first: they use a data basis that applies administrative data that is already widely used. Second, the data is very complex in terms of sources and its genesis so that advice in regard to data cleansing and the question of robustness of the results may be useful. Third, the authors provided access to the majority of their program codes which makes a reconstruction of the basic procedure in cleansing the data feasible. Finally, this approach of cleansing the data appears innovative and may therefore be of interest for other researchers and users of administrative data - in particular when using data with a high number of overlaps.

The idea of this investigation in this paper is to adapt a reference procedure including the data cleansing and the estimations of the interested outcome and then cause variations in the underlying data cleansing while holding the database and the method as far as possible constant. This would allow identifying any difference in the outcome measure as a result of the cleansing itself. With respect to the data structure variation mainly focuses on handling parallel observations. In order to cope with this issue the observations on the individual level are regarded within time frames for which the cleansing rules can be applied. Furthermore, since every observation has specific qualities as length and source of information this information is used as the major characteristics of the data cleansing. The cleansing finally aims to identify one valid state for each time window and finally transform the data into a panel data set.

The setting of the data cleansing

The data cleansing consists of two parts. The first part concentrates on separating the longitudinal data into time windows of two weeks. Each time window may then consist of several parallel or overlapping episodes of the observations, which may differ in terms of length and source. In order to isolate one state out of the parallel ones sorting rules are applied so that an order of precedence is made where in the second part one certain state can be picked up. Two ordered sorting rules exists in the first part:

1. *Sorting Rule 1 (Length Priority):* First all parallel episodes are sorted by length.

2. *Sorting Rule 2 (Source Priority):* If two or more parallel episodes have the same length (within the two-week time window) the respective data source is used as a proxy of the validity to order the observations.

Sorting the overlapping episodes in a certain way is the key for the whole cleansing procedure. However, this investigation only concentrates on the second rule. This in turn means that rule 1 will not be changed and variance is only caused by changing the order of the importance of the sources. To some extent this refers to changing the trust in the validity and reliability of the sources. In part two, after having ordered the episodes, only one general rule exists to select the final state:

> *Selecting Rule (Source Priority):* Out of states 1 and 2 the final one is selected by applying predefined specific rules which base on the priority of the respective source.

For the benchmark the classification of the sorting priorities of the sources follows the approach of the reference study and is for the rest of this paper referred to as procedure V0. In this procedure participation in a labor market program gets the highest priority because it is in the heart of the evaluation design. Sources associated with payments (which are the benefit-recipient-history and the employment- history) are regarded as relatively reliable and follow on second and third place. The job search register with lots of optional information is considered to be less reliable with respect to begin and end dates and has therefore the lowest priority.

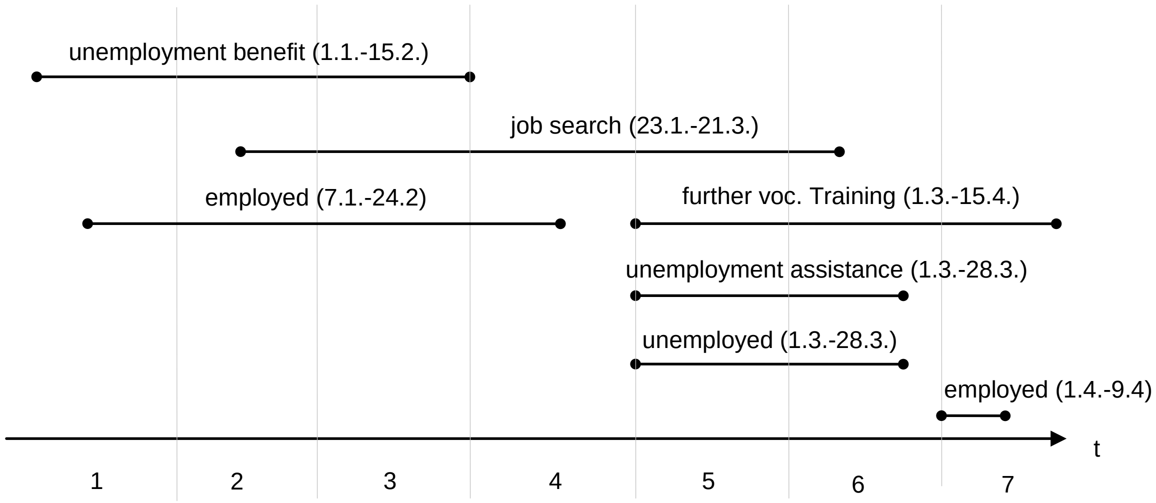
Figure 1 illustrates and describes this procedure. Imagine that the upper panel of the figure is an abstraction of an individual employment history that can be observed in the IEB. Each line represents an observation of a certain employment state (wage work, receiving unemployment benefits, employment search,..) with begin and end date in parentheses. What one can see is that several parallel observations exist (some may be legally allowed others not) coming from the same source of information, from different sources or even combinations of this. For example it is legally possible to be employed and at the same time searching officially for a job (two sources, legal combination) but it is not permitted to be fulltime employed and receive unemployment benefit at the same time. The legitimacy of some combinations can vary due to changes in the laws, which means that also the time of appearance has to be taken into consideration.

The x-axis represents time and is divided into (seven[4]) time windows of two weeks. These time windows built the basis for the number of observations that will be isolated. Furthermore seven observations are reported during the whole period of observation. As one can see there is a benefit-observation lasting from time-frame one until the end of time-frame three and an employment[5]-observation beginning in time-frame one and ending in the mid of time-frame four. The data cleansing now aims to define one single unique employment status for each time window. This is displayed in the lower panel of Figure 1 which consists of a table that shows the transformation of the observations into the different states. Each column is representing one time-frame. The rows contain the different states in that frame (e.g. time-frame one - see T1 - covers two states and frame five contains four states - see T5).

[4] The number is just for illustrative reasons

[5] For the sake of simplicity the sort of observations is here described in a highly aggregated manner - like employed – irrespective of the particular values, which are used in the procedures.

Figure 1: example of individual's history with overlaps



	T1	T2	T3	T4	T5	T6	T7
State1	benefit	benefit	benefit	search	training	training	training
State2	employed	employed	employed	employed	assistance	assistance	employed
State3		search	search		search	unemployed	
State4					unemployed	search	
…							
Final state	benefit	benefit	benefit	employed	training	training	training

As mentioned above, the most important step in the data cleansing approach refers to the sorting routines. Therefore the order of state across the column displayed in the table of Figure 1 is crucial. For example the first column displays two episodes from different sources, one from the receipt of benefit source and the other from the employment histories. The first row contains the longest episode in the time frame. If multiple episodes with the same length are observed the episodes are sorted by heuristic routines (see time-frame five). All episodes with participation in a training scheme are classified with the highest priority, since the evaluation of them is the main point of interest in a program evaluation study. For not being associated with any type of payment episodes out of the job search register (two possible states: searching and unemployed) are considered as less valid and are therefore classified with a lower priority.

After having identified the first two states in step one they are now processed in the second step of the data cleansing. The final state is now selected by applying the selecting rule out of the first two episodes. Even though for simplicity it is talked about the priority of the four sources at this point, the selecting rule implies a significant number of rules that define which state to prefer: for example participation in a degree course (program) beats subsistence allowance (program) when they are parallel, but not being unemployed and searching for a job (job search register) compared to subsistence allowance at the same time leads to the final state of subsistence allowance.

To demonstrate the choice of the final state the example continues in the last row of the table in Figure 1. In time window two (column T2) episodes of observations from the unemployment benefit register and the employment history occur. Following the rules of priority the first state is defined as the final state. Likewise, in period five (column T5) the final state (further vocational training) arises because unemployment assistance has a lower priority than the participation in a labor market program. Note that not always the first state is chosen as the final state (see T4). If the source of state 2 has a higher priority than the source of state one, the final state would be the one of state 2. This is displayed in time window four, where the final state is employment, because being employed has a higher priority than searching for a job. As mentioned above this is just a very simple description of the applied rules to illustrate the approach.

4 The development of Cleansing Procedures

To examine whether cleansing procedures have a noteworthy impact on estimation results in the following the benchmark procedure (V0) is modified in different ways to develop new procedures. Subsequently the whole data cleansing and preparation is done with the new procedures. This results in new evaluation samples that are compared with the benchmark sample of V0.

As described in section 3 the procedure consist of two main sorting rules. Rule 1 orders the observations per time-frame by length which remains stable for all procedures. However, altering the priorities of the data sources the final state may be changed in many directions. First, there can be an effect on the employment history, e.g. on the length and number of un/employment periods. Second, the selection into programs may be affected, the point in time (displacement) and the participation in general. Above all, the outcome is probably influenced by means of duration and moment of un/employment periods.

Notice rule V0 consists of the following order: training – benefit – employment – applicant. This is now changed in two different ways:

- The first variation leads to procedure V1 (sorting rule: training – employment – benefit – applicant), where participation in a labor market program still has the highest priority because in the estimation at the end this is the interest of the labor market researcher. The major difference to V0 is that the priority of the two sources with money payments (Benefit-Recipient-History; Employment History) is reversed. As mentioned above both are regarded as reliable because they include payments (benefits; wages) which have to be precise. The lack of a clear indication which one is better in terms of accuracy and therefore which one to prefer is a sufficient reason to analyze the impact of changing the priority. As a potential effect changing the position of employment and benefit information in the sorting procedure gives employment information in V1 an extra weight compared to V0. Therefore a higher number and longer durations of employment episodes in the panel data of the analysis sample can be expected.

- Procedure V2 (sorting rule: employment – training – benefit – applicant) assumes the participants-in-measure database as not fully valid because it is possible that a participant dropped out of the measure without correcting it in the data or a measure has been rescheduled and in the data occur both observations without an identification mark which one is the right one. Thus, it downgrades the priority of this data. However, since participations can come along with benefit and the interest of any evaluation focuses on the effects of participation they are not downgraded completely, but ordered as priority two. Assigning them behind benefit receipt leads to a dramatic reduction of the number of participations used for subsequent evaluation studies.[6] Therefore participations in training measures are ordered behind employment and before benefit receipt. Applicants-Pool data remain with the lowest level of priority because there are no payments involved and the state 'job-searching but not unemployed' can be parallel with nearly every other state and has no additional information. Applying this sorting rule the employment episodes gain an extra weight and observations for the treatment group may be 'lost' in the control groups favor. Caution is advised in the special context of program evaluation because this relates to a problem that can be described as an increase of unobserved substitutes in the pool of the potential counterfactuals.

The consequences of the different procedures for the example can be seen in Table 1. For each procedure the row with the final states is shown. The respective order of priority is heading each row.

Table 1: Variation in the final states

	T1	T2	T3	T4	T5	T6	T7
V0: training – benefit – employment – applicant							
Final state	benefit	benefit	benefit	employed	training	training	training
V1: training – employment – benefit – applicant							
Final state	employed	employed	employed	employed	training	training	training
V2: employment – training – benefit – applicant							
Final state	employed	employed	employed	employed	training	training	employed

6 This has been tested in a so called naive model which is not shown.

Comparing the final states of sample V1 in reference to sample V0 leads to changes in the first three time-frames. The states for the other periods remain the same. This is exactly what one would expect when reversing the priority of the Employment History and the Benefit-Recipient History and may therefore have a considerable impact on the employment history before and after program participation. Comparing V2 to V0 the changes from benefit to employment in the first three periods remain like in V1 because being employed is still of higher priority than receiving benefit. Additionally one of the three periods of training participation changes into employment which is in line with the expected pattern. Furthermore, drop-outs of labor market programs are now taken into consideration and the individual is earlier employed then in V0.

5 Results

5.1 Descriptive statistics

To assess the influence of the different cleansing procedures on the real data the evaluation samples with the different underlying order of priority are compared. A first step for this investigation is testing differences of the sample means always in reference to the benchmark sample V0. This is done for different programs. Therefore, before starting the comparisons see Table 2 which reports a brief description of the type of programs.

Table 2: Description of programs

Program type	Description	Mean planned duration (days)
Jobseeker assessment (JSA)	Assessment of jobseekers' ability and willingness to search for job and to work, basic job search assistance.	38
Short training (ST)	Minor adjustment of skills.	49
Short combined measures (SCM)	Acquisition of specific knowledge and skills	55
Job-related training (JRT)	Combined off-the-job and on-the-job training in a specific field of profession.	184
General further training ≤ 6 months (GT6)	General update, adjustment and extension of knowledge and skills; mainly off the job, planned duration ≤ 6 months	119
General further training > 6 months (GT6+)	General update, adjustment and extension of knowledge and skills; mainly off the job, planned duration > 6 months	308
Degree course (DC)	Vocational training that awards a formal professional degree and that corresponds to regular vocational training in the German apprenticeship system.	692

Note: The mean planned duration is calculated based on the total inflow into unemployment between January 2000 and December 2002

The last four programs in Table 3 (JRT, GT6, GT6+, DC) are part of the so called Further Vocational Training. In the following the results for these programs are displayed and discussed in detail whereas the first three programs of Table 2 (ST, SCM, JSA) belong to the group of training measures and are due to space restriction not displayed or discussed here[7] unless they are important for the overall result (interactions). Also notice that the terminus 'participants' in this study only covers individuals who have started a program during the next

[7] The results for these programs can be found in the Appendix.

18 months after becoming unemployed and have received unemployment benefits directly before the program start.

In Table 3 selected descriptive statistics are presented for all three samples. The selection is based on the difference to the benchmark and only the ones with difference greater than one percentage point are displayed.[8] The table displays the total of participants and other variables for the benchmark in column two and for the two variations V1 and V2 in column three and four.

Table 3: Totals and shares of selected variables

Model / Variable	V0	V1	V2
		DC	
number of observations	503	453	447
no child	75.35	74.61	73.73
1 child	13.92	15.23	15.89
completed apprenticeship	44.73	43.05	43.49
industry of last job: service	36.98	35.10	34.66
program start in 2000	20.87	22.96	22.52
program start in 2002	38.97	37.53	37.53
		GT6+	
number of observations	952	903	898
occupational status in last job: clerk	51.05	52.16	52.48
program start in 2000	24.68	25.80	25.58
months unemployed till treatment 1-3	40.23	41.31	41.46
		GT6	
number of observations	684	653	641
months unemployed till treatment 1-3	43.71	45.65	45.06
months unemployed till treatment 13-24	6.29	4.89	5.09
monthly earnings last job: 750-1000 €	28.36	26.87	27.01
		JRT	
number of observations	736	673	658
single	37.64	38.55	38.74
occupational status in last job: clerk	25.54	26.59	27.18
program start in 2000	21.47	22.60	22.67

[8] For a full list of variables and statistics please contact the author.

program start in 2001	38.59	39.59	39.49
program start in 2002	39.95	37.81	37.84
remaining benefit claim >9 months	22.15	23.34	23.12
monthly earnings last job: 750-1000 €	28.67	27.62	27.63
monthly earnings last job: 1000-1250 €	18.75	19.79	19.67
months unemployed till treatment 1-3	36.01	38.40	38.44
months unemployed till treatment 7-12	27.17	26.29	26.13
months unemployed till treatment 13-24	8.97	7.83	7.96

Except of the totals all entries are in percent.

As presumed before the number of observations decreases in all treatment groups. Besides personal characteristics like the number of children (shift from no child to one child) or the occupational status of the last job (increasing share of clerks) especially the time-dependent variables show strong differences between the samples and for all types of program. The program start for example appears in the samples V1 and V2 more often in 2000 than in 2002 or the time an individual is unemployed until starting a program decreases.

These differences can occur due to two reasons: a different composition of the samples or the use of another observation for the same individual with different information in case of parallelism. To examine this in Table 4 the movements of individuals between the samples V0 and V1 are displayed. See for example the first row in Table 4 which reports that 1,020 individuals in program ST are observed based on procedure V0. Applying procedure V1 yields to 941 individuals in this program. Compared to V0 this makes a loss of 79 individuals (-92 drops-outs, see the last column; +14 new, see last but one row). However, the majority of the participants of ST in V0 (90%) are again in ST when applying V1, only one individual is now participating in JSA instead of ST and two are now in the control group (non-participants, NP).

It can be seen that a large share of all individuals (91%) participates in the same type of program in V1 as they did in V0 and 86% of the non-participants (NP) are also not participating in a program in V1. Therefore a change in the underlying data cleansing does not lead to an overall change of the sample as well as the out-dropping participants are not moving into the group of the non-participants. The transition into other types of programs is negligible (single cases). These results for V2 are analog[9].

[9] Table A2 in the appendix

Table 4: Transition (V0 to V1)

V0		V1								
	total (row)	**ST**	**SCM**	**JSA**	**JRT**	**GT6**	**GT6+**	**DC**	**NP**	**drop outs**
ST	**1,020**	925 (90%)	0	1	0	0	0	0	2	92 (9%)
SCM	**1,252**	1	1,138 (91%)	0	1	1	0	0	0	111 (9%)
JSA	**1,415**	0	0	1,272 (90%)	1	1	0	3	3	135 (9,5%)
JRT	**736**	0	0	0	658 (89%)	0	0	1	2	75 (10%)
GT6	**684**	0	1	2	0	637 (93%)	1	0	1	42 (6%)
GT6+	**952**	0	1	1	0	3	889 (93%)	0	1	57 (6%)
DC	**503**	0	0	0	1	2	1	441 (88%)	0	58 (11,5%)
NP	**17,734**	1	3	1	3	2	3	0	15,254 (86%)	2,467 (14%)
new	645	14 (2%)	13 (2%)	20 (3%)	9 (1%)	7 (1%)	9 (1%)	7 (1%)	566 (88%)	
	total (column)	**941**	**1,156**	**1,297**	**673**	**653**	**903**	**452**	**15,829**	3,037

Note: the percent in parenthesis which relate to the rows are rounded and do therefore not necessarily need to sum to 100 over the rows

To sum up the distinctions in the descriptive statistics occur due to 2 reasons: sample composition (different individuals) and use of different observations (same individuals). More precisely, because the composition of the sample does change, even though in a rather small extent, the differences in the mean personal characteristics can be ascribed to the drop outs and new observations which lead to the new composition. Whereas the differences in the time-dependent variables do not occur because of different individuals but due to changes of the final states and therefore of a prolongation or shortening of un/employment episodes. For example the increasing number of children is very likely to be a result of the 10% new individuals in the sample whereas the decreasing time until treatment can be traced back to a shifting of begin and end dates of un/employment observations of the same individuals. These results can be confirmed by having a closer look on single individuals, where the duration of employment is up to 10 months longer in V1 for the same individual in comparison to V0. On average these difference nearly balance to a difference of about 1 month.

5.2 Effect on the estimation results

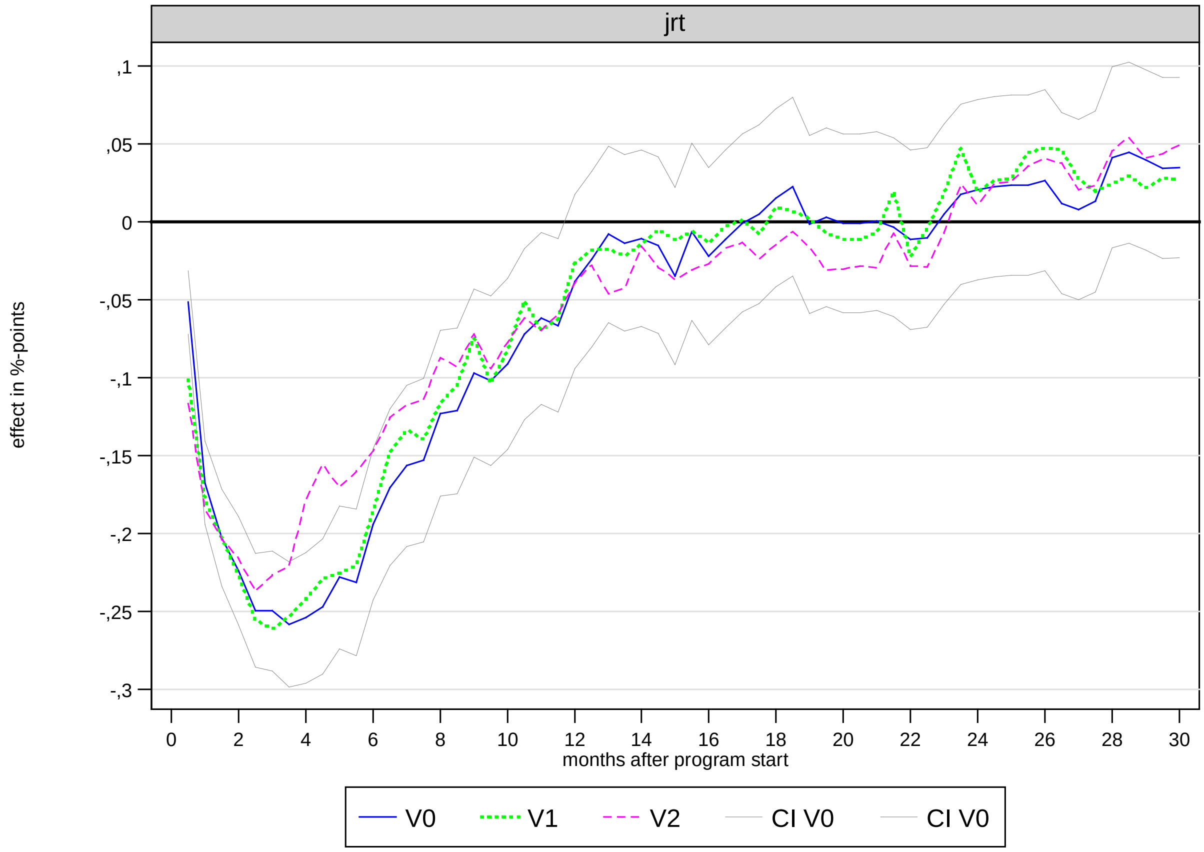
As reported above, differences remain low concerning average characteristics between the sample populations that result from the different cleansing procedures. This may also indicate that outcome differences are also negligible with respect to causal effects. However, differences occur in multiple ways. Therefore the impact of different cleansing methods is tested by conditioning on a specific subpopulation that is sampled due to a matching framework[10] which is a frequently used evaluation method and also used by Wunsch and Lechner (2008) in their study. To some extent matching in this context performs a conditional non-parametric regression in which the mean outcome difference on the treatment is regressed conditional on a similar subset of individuals. The algorithm (Epanechnikov-Kerrnel-Matching) is kept constant for the 3 models, only the underlying samples are different due to the cleansing procedures applied before. This method estimates the employment chances of participants of labor market programs compared to individuals who did not participate (control group). By using individuals with the same or similar characteristics from both groups conclusion can be made how participants would have performed if they had not participated ('Average Treatment Effect on the Treated' – ATT).

In Figure 2 the effects of participation in 'job-related training' (JRT) compared to non-participation are displayed for all 3 models to illustrate the impact of the cleansing procedures on the estimation results[11]:

Figure 2: Effects of program participation compared to non-participation

[10] For details and a deeper discussion see Rosenbaum/Rubin, 1985; Heckman et al., 1998; Imbens 2004; Caliendo and Kopeining, 2008.

[11] See the appendix for the results of the further program types.



For illustrative reasons the first focus is on the general pattern of the program outcome. The reported effects are calculated on a monthly basis starting at the beginning of the treatment and show the ATT with respect to the employment status. The continuous lines (blue, gray) show the ATT and the confidence interval for the benchmark V0. The dashed and dotted lines (green, pink) display the ATT's that base on the samples created by the varied cleansing procedures (V1, V2). Negative values (equals negative effects) denote worse employment chances for participants compared to non-participants. Positive values in contrast imply better chances to be employed after having participated in a program.

What can be seen now from Figure 2 is that all procedures almost show the same pattern of the ATT over time. During the first period treated individuals are locked-in the program which means they are participating and are therefore not able to be employed (month 0-6). This then relaxes as participants exit the program and their chances to find a job and be employed improve (recovery period; month 6-13). The program is pretty long and so the recovery is very slow. This implies a low ATT at the end of the observation period but with a slight upward trend. The effects of the varied procedures V1 and V2 differ a bit. V1 only shows minor differences whereas V2 has higher values especially during the lock-in effect[12] and thereafter is worse or equal to the benchmark V0, But almost all differences lie within the confidence interval of V0. Even though the values of V2 recover faster during the lock-in ef-

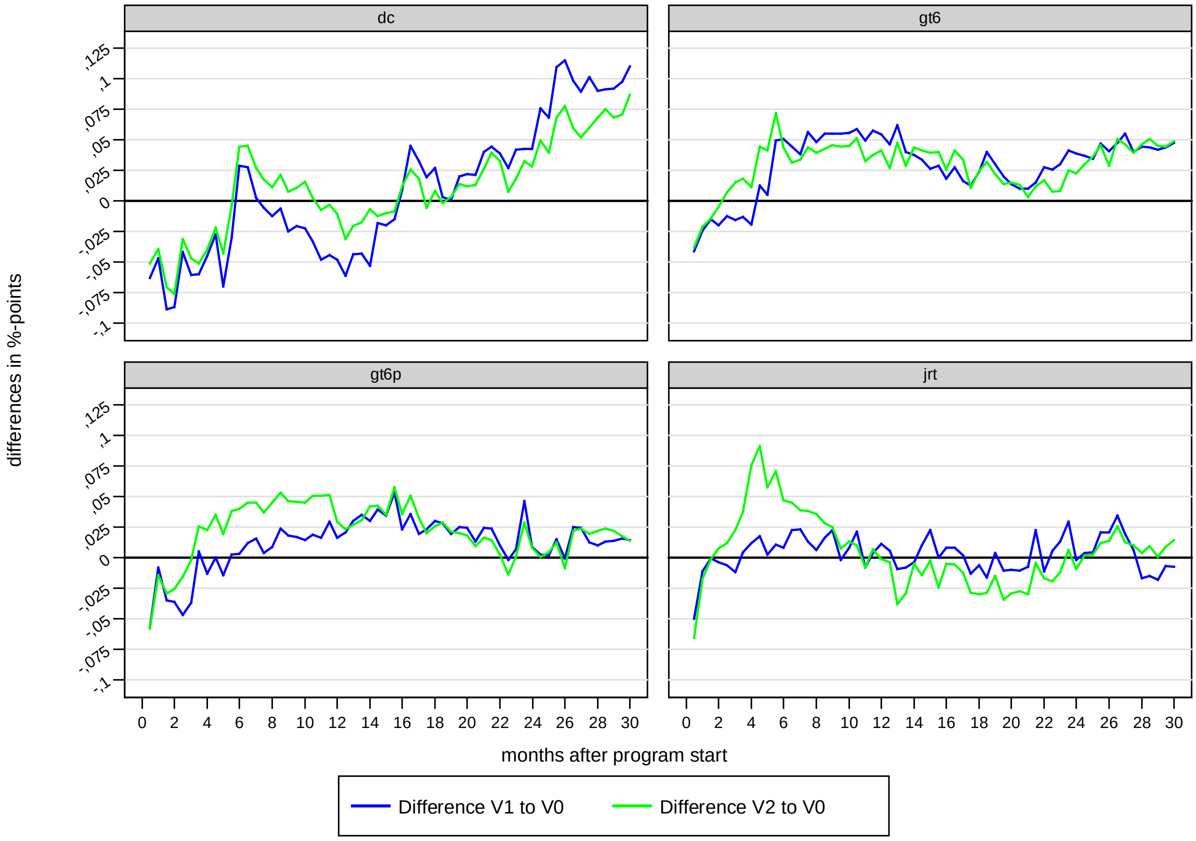
[12] In the terminology of van Ours (2004) lock-in effects are negative employment and earnings effects in the short run, which are directly related to programme duration.

fect the overall recovery period is not faster than the one of V0. To evaluate the impact of the different procedures on the results a closer look on these differences in reference to V0 is taken.

In Figure 3 the differences between the ‘Average Treatment effects on the Treated’ (ATT) with respect to employment for the different procedures (V1, V2) to the benchmark V0 are displayed. They are calculated on a monthly basis starting at the beginning of the treatment and again for illustrative reasons only the four programs which belong to Further Vocational Training are shown.

As one can see, the difference between model V1 and the benchmark V0 reveals negative values in the beginning of the lock-in effect (up to -0.05) before it becomes (and stays) positive up to a maximum of 0.055 percentage-points or it has alternating sign in a smaller range (-0.0125 to 0.025). An exception to this is DC where the extent is way larger, it starts with a maximum negative value of 0.09 in the beginning of the lock-in effect, followed by a rapid increase (0.025) and a further decline before the difference to the benchmark increases considerably up to a value of 0.11 percentage points. This means that the employment chances of participants in degree courses compared to non-participants are 11 % higher using model V1 - which prefers employment over benefit - than the benchmark or they are not remarkably differing like in JRT.

Figure 3: Differences between ATT's



Comparing the estimation results of model V2 and the benchmark V0 yields similar findings as described for the difference V1 to V0. Deviating from these results are much higher differences occurring during the lock-in effect for all types of program. A possible explanation is the priority of the data source and therefore the change of sorting-rule two and the selecting rule. V0 grants program participation the highest priority and employment is ordered on third position. In V2 being employed is preferred to program participation in cases of parallel information. When the program starts the effect for V2 recovers quickly and differs from V0 in different amounts over the program types with a maximum of 0.09 percentage points for job related training (JRT). This could be due to participants who dropout earlier and start to work. The dropout is not always (seldom) registered and therefore two parallel observations occur in the data. V0 continues counting this as participation whereas in V2 employment is the final state and therefore the lock-in effect decreases and therefore the difference increases. Shortly after the lock-in the values are either almost identical (GT6+, GT6) or somewhat lower (JRT, DC) to difference one. This means the employment chances are approximately 0.01 to 0.05 percentage-points higher (up to 0.085 for DC) using model V2 then the benchmark. Only for JRT the chances are lower (0.01 to 0.026 %-points) between month 11 and 24 after program start.

While Figure 3 shows the time depending pattern of the ATT also the cumulated effects of program participation over a certain period of time is analyzed. This investigation allows to study whether low differences at single points in time may cause significant differences over time. Results are reported in Table 6. As it can be easily seen the participants face losses over the 30-month observation period in unsubsidized employment for all programs and models between 2 months for the shorter and 10 months for longer programs (DC). The differences between the models are positive but not substantial and vary between 0.07 and 0.88 months. This means that even the big differences during the lock-in effects balance over time.

Table 6: Cumulated effects and differences (in months)

program / model	JRT	GT6	GT6+	DC
V0	-1.76	-2.59	-6.12	-9.82
V1	-1.70	-1.71	-5.80	-9.55
V2	-1.62	-1.71	-5.47	-9.46

6 Summary and Conclusion

The influence of variations in data cleansing on overlaps in a merged administrative data set on estimation results is a crucial issue due to the complexity of these data. Different data preparation might lead to different analysis samples and thus cause effects on estimation results. This study presents different cleansing procedures and the effects of data cleansing that yield to distinctive analysis samples and compares the descriptive and the estimated program effects for participants in German labor market programs based on these samples.

In a first step a benchmark is build using the data preparation approach applied in Wunsch and Lechner (2008) before in a second step two variations of the cleansing procedures are developed and applied by changing the priority order of the data sources. Therefore in cases of overlapping observations the selecting rule – which observation to take - changes and thus also the final states at these points in time. Afterwards, the influence of these different procedures on the resulting samples is tested using mean comparison tests. These tests show that there are differences in the personal and time dependent characteristics but not to a remarkable extent, which is consistent with the findings of previous studies (e.g. Waller 2008). The composition of the evaluation sample remains almost the same (91%) and seems to be therefore unaffected by the cleansing procedures.

Finally the impact of the different cleansing procedures on point estimates of matching algorithms is investigated and a sensitivity analysis is done. The findings emphasize the results of the mean comparison tests and differ between the types of program, over time and over the procedures. Generally the differences are of remarkable extent primarily during the lock-in effect, especially in the longer programs, and in a lesser degree at the end of the observation period. The first might be of minor importance if one is interested in long-term effects only but the latter may be of practical importance. The cumulated effects over the whole observation period balance the differences at the single points in time and do not differ in a notable extent.

Therefore the results show that data cleansing has to be done carefully and simple deliberate rules are necessary. Not only sensitivity analysis and robustness checks for the evaluation method should be an essential part of each evaluation but also the data cleansing has to be tested, if someone is using administrative data with overlapping periods. At least 2 different variants of data cleansing should be done to assess the influence on the results. A transition matrix displays possible displacements of the sample and can reveal possible weaknesses of the further results because the composition and creation of treatment and control group is a crucial part of evaluation methods. However, time and efforts to apply and check different cleansing procedures should not exceed the benefits out of it. Consequently administrative data approved their importance and the extensive use as a source for research. Results gained by evaluation based on them are (relatively) robust to changes in the data cleansing procedures in matters of overlaps as long as they are not completely beside the point.

References

Ashenfelter, O. (1978): Estimating the Effect of Training Programs on Earnings, in: The Review of Economics and Statistics, 60(1), 47-57

Angrist, J.D. (1998): Estimating the Labor Market Impact of Voluntary Military Service Using Social Security Data on Military Applicants, in: Econometrica, 66(2), 249-288

Bauer, T., Bonin, H., Sunde, U. (2007): Real and Nominal Wage Rigidities and the Rate of Inflation: Evidence from German Micro Data, IZA Discussion Paper, 959.

Bernhard, S., Dressel, C., Fitzenberger, B., Schnitzlein, D., Stephan, G. (2006): Überschneidungen in der IEBS: Deskriptive Auswertung und Interpretation, FDZ Methodenreport, 04/2006

Biewen, M., Fitzenberger, B., Osikominu, A., Waller, M. (2007): Which Program for Whom? Evidence on the Comparative Effectiveness of Public Sponsored Training Programs in Germany, IZA Discussion Paper, 2885

Blank, R. M., Charles, K. K., Sallee, J. M. (2009): A Cautionary Tale About the Use of Administrative Data: Evidence from Age of Marriage Laws, in: American Economic Journal: Applied Economics, 1(2), 128-149

Caliendo, M., Kopeinig,S. (2008): Some Practical Guidance for the Implementation of Propensity Score Matching, in: Journal of Economic Surveys, 22(1), 31-72

Carling, K., Richardson,K. (2004): The relative efficiency of labour market programs: Swedish experience from the 1990s. in: Labour Economics, 11(3), 335-354

Eliason, M., Storrie, D. (2006): Lasting or Latent Scars? Swedish Evidence on Long-Term Effects of Job-Displacement. In: Journal of Labour Economics, 24(4), 831-856

Engelhardt, A., Oberschachtsiek, D., Scioch, P. (2008): Datengenese zweier Datenkonzepte: MTG (Maßnahme-Teilnahme-Grunddatei) und ISAAK (Instrumente Aktiver Arbeitsmarktpolitik). Eine Betrachtung ausgewählter Fälle am Beispiel der Förderung im Rahmen des ESF-BA-Programms, FDZ Methodenreport, 08/2008

Fitzenberger, B., Osikominu, A., Völter, R. (2006): Imputation Rules to Improve the Education Variable in the IAB Employment Subsample, in: Schmollers Jahrbuch, 126, 405-436

Fitzenberger, B., Osikominu, A., Völter, R. (2009): Get Training or Wait? Long-Run Employment Effects of Training Programs fort he Unemployment in West Germany, in: Annales d'Economie et de Statistique, (forthcoming)

Fitzenberger, B., Speckesser, S. (2007): Employment Effects of the Provision of Specific Professional Skills and Techniques in Germany, in: Empirical Economics, 32(2), S. 529-573

Fitzenberger, B., Wilke R. A.: (2009) Unemployment Durations in West-Germany Before and After the Reform of the Unemployment Compensation System during the 1980s, in: German Economic Review, (forthcoming)

Geerdsen, L., Holm, A. (2004): Job-search Incentives from Labor Market Programs – an Empirical Analysis, Centre for Applied Microeconometrics Working Paper, 2004-03, University of Copenhagen

Groves, R. M., Fowler, F. J., Couper, M. P., Lepkowski, J. M., Singer, E., Tourangeau, R. (2004): Survey Methodology. John Wiley & Sons, Ltd.

Groves, R. M. (2004): Survey Errors and Survey Costs. John Wiley & Sons, Ltd.

Hämäläinen, K., Ollikainen, V. (2004): Differental Effects of Active Labour Market Programmes in the early stages of young people's unemployment, VATT Research Reports 115

Heckman, J. J., Ichimura, H., Todd, P. E. (1998): Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme, in: The Review of Economic Studies, 65(2), 261-294

Hotz, V. J., Scholz, J. K. (2001): Measuring Employment and Income for Low-Income Populations with Administrative and Survey Data. IRP Discussion Paper, 1224-01

Hujer, R., Caliendo, M., Thomsen, S. L. (2004): New evidence on the effects of job creation schemes in Germany--a matching approach with threefold heterogeneity, in: Research in Economics, Elsevier, 58(4), 257-302

Imbens, G. W. (2004): Nonparametric Estimation of Average Treatment Effects under Exogeneity: a Review, in: The Review of Economics and Statistics, 86(1), 4-29

Jabine, T. B., Scheuren, F. (1985): Goals for Statistical Uses of Administrative Records: The Next 10 Years, in: Journal of Business & Economic Statistics, 3(4), 380-391

Jacobebbinghaus, P., Seth, S. (2007): The German integrated employment biographies sample IEBS. In: Schmollers Jahrbuch. Jg. 127, H. 2, S. 335-342

Jaenichen, U., Kruppe, T., Stephan, G., Ullrich, B., Wießner, F. (2005): You can split it if you really want: Korrekturvorschläge für ausgewählte Inkonsistenzen in IEB und MTG, FDZ Datenreport, 04/2005

Jenkins, P. S., Lynn, P., Jäckle, A., Sala, E. (2005): Linking Household Survey and Administrative Record Data: What Should the Matching Variables Be?, DIW Discussion Papers, 489,

Johansson, P., Skedinger, P. (2005): Misreporting in register data on disability status: evidence from the Swedish Public Employment Service, in: Empirical Economics, 39(2), 411-434

Klose, C., Bender, S. (2000): Berufliche Weiterbildung für Arbeitslose – ein Weg zurück in Beschäftigung? Analyse einer Abgängerkohorte des Jahres 1986 aus Maßnahmen zur Fortbildung und Umschulung mit einer ergänzten IAB-Beschäftigungsstichprobe 1975-1990, Mitteilungen aus der Arbeitsmarkt- und Berufsforschung, 24, 421-444

Kluve, J., Card, D., Fertig, M., Gora, M., Jacobi, L., Jensen, P., Leetmaa, R., Nima, L., Patacchini, E., Schaffner, S., Schmidt, C. M., van der Klaauw, B., Weber, A.(2006): Active Labor Market Policy in Europe: Performance and Perspectives, Springer: Berlin et al., 2007.

Kruppe, T., Oertel, M. (2003): Von Verwaltungsdaten zu Forschungsdaten-Die Individualdaten für die Evaluation des ESF-BA-Programms 2000-2006. IAB Werkstattbericht

Köhler, M., Thomsen, U. (2009): Data integration and consolidation of administrative data from various sources * the case of Germans' employment histories. In: Historical Social Research, 34(3), 215-229.

Kruppe, T., Müller, E., Wichert, L., Wilke, R. A. (2008): On the Definition of Unemployment and its Implementation in Register Data - The Case of Germany, in: Schmollers Jahrbuch. 128(3), 461-488

KVI: Kommission zur Verbesserung der informationellen Infrastruktur zwischen Wissenschaft und Statistik (Hg.) (2001): Wege zu einer besseren informationellen Infrastruktur. Gutachten der vom Bundesministerium für Bildung und Forschung eingesetzten Kommission zur Verbesserung der informationellen Infrastruktur zwischen Wissenschaft und Statistik, Baden-

Baden (mit CD-ROM mit 41 Expertisen und Beiträgen, die im Auftrag der Kommission bzw. im Zuge der Kommissionsarbeiten erstellt wurden).

Lechner, M., Miquel, R. (2009): Identification of the effects of dynamic treatments by sequential conditional independence assumptions. In: Empirical Economics, online first

Lechner, M., Miquel, R., Wunsch, C. (2004): Long-Run Effects of Public Sector Sponsored Training in West Germany, IZA Discussion Paper, 1443

Mueser, P. R., Troske, K. R., Gorislavsky, A. (2007): Using State Administrative Data to measure Program Performance, in: The Review of Economics and Statistics, 89(4), 761-783

Osikominu, A. (2008): Is Short Training Short-Lived and Long Trainig Long-Lasting? A Multi-State Duration Analysis of the Dynamic Effects of Training Schemes fort he Unemployed, mimeo, Albert-Ludwigs-University Freiburg

Pyy-Martikainen, M., Rendtel, U. (2008): Assessing the impact of initial nonresponse and attrition in the analysis of unemployment duration with panel surveys, in: AStA, 92, 297-318

Reimer, M., Künster, R. (2004): Linking job episodes from retrospective surveys and social security data: specific challenges, feasibility and quality of outcome. Berlin: Max-Planck-Institut für Bildungsforschung. (Arbeitsberichte Max-Planck-Institut für Bildungsforschung, Forschungsbereich Bildung, Arbeit und gesellschaftliche Entwicklung; 2004, 8)

Rendtel, U., Nordberg, L., Jäntti, M., Hanisch, J., Basic, E. (2004): Report on quality of income data, CHINTEX Working Paper, 21

Rinne, U., Uhlendorff, A., Zhao,Z. (2008): Vouchers and Caseworkers in Public Training Programs: Evidence from the Hartz Reform in Germany, IZA Discussion Papers, 3910

Roed, K., Raaum, O. (2003): Administrative Registers - Unexplored Reservoirs of Scientific Knowledge? In: The Economic Journal, 113, 258-281

Rosenbaum, P. R., Rubin, D. B. (1985): Constructing a Control Group Using Multivariate Matched Sampling Methods that Incorporate the Propensity Score, in: The American Statistician, 39(1), 33-38

Seysen, C. (2009): Effects of changes in data collection mode on data quality in adminstrative data * the case of participation in programmes offered by the German Employment Agency. In: Historical Social Research, 34(3), 191-203.

Stephan, G. (2008): The effects of active labor market programs in Germany * an investigation using different definitions of non-treatment in: Jahrbücher für Nationalökonomie und Statistik, 228, H. 5/6, 586-611

van den Berg, G. J., Lindeboom, M., Dolton, P. J. (2004): Survey Non-Response and Unemployment Duration, IZA Discussion Papers, 1303

van Ours, J. (2004): The Locking-in Effect of Subsidized Jobs, in: Journal of Comparative Economics, 32, 37-52

Waller, M. (2008) On the Importance of Correcting Reported End Dates of Labor Market Programs, in: Schmollers Jahrbuch, 128, 213-236

Wallgren, A., Wallgren, B. (2007): Register-based Statistics – Administrative Data for Statistical Purposes. John Wiley & Sons, Ltd.

Wunsch, C., Lechner, M. (2008): What did all the money do? On the General Ineffectiveness of Recent West German Labour Market Programmes, in: Kyklos, 61(1), 134-174

Appendix

Table A1: descriptive results for Training Programs

Model / Variable	V0	V1	V2
	ST		
number of observations	1,020	941	917
female	49.61	47.61	48.06
no child	60.78	62.38	62.15
1 child	19.71	17.96	18.17
looking for fulltime-job only	77.75	78.85	79.35
occupational status in last job: clerk	42.65	43.46	43.76
program start in 2002	12.06	11.26	10.97
months unemployed till treatment 1-3	43.92	42.72	42.69
	SCM		
number of observations	1,252	1,156	1,118
looking for fulltime-job only	76.68	77.42	77.74
last occupation: services	37.54	36.33	36.66
program start in 2002	39.14	38.06	38.52
months unemployed till treatment 1-3	35.62	36.85	36.57
months unemployed till treatment 10-12	28.83	27.68	28.18
	JSA		
number of observations	1,415	1,297	1,249
qualification in desired job: skilled	42.69	43.41	43.85
monthly earnings last job: 500-750 €	25.72	24.21)	24.37
months unemployed till treatment 1-3	40.14	42.95	42.35
months unemployed till treatment 10-12	25.23	22.90	22.95
	NP		
number of observations	17.734	15,829	15,276
last occupation: services	36.32	34.88	34.73
months unemployed till treatment 4-6	58.85	62.41	61.49
months unemployed till treatment 10-12	31.10	27.20	28.00

All entries are in per cent. Differences to V0 are displayed in percentage points in parentheses.

Table A2: Transition (V0 to V2)

V0		V2								
	total (row)	**ST**	**SCM**	**JSA**	**JRT**	**GT6**	**GT6+**	**DC**	**NP**	**drop outs**
ST	**1,020**	906 (89%)	0	1	0	0	0	0	7	106 (10%)
SCM	**1,252**	2	1,107 (88%)	0	1	1	0	0	5	136 (11%)
JSA	**1,415**	2	1	1,238 (87%)	0	0	0	3	11	160 (11%)
JRT	**736**	0	0	1	650 (88%)	0	0	3	3	80 (11%)
GT6	**684**	0	1	1	1	629 (92%)	1	0	1	50 (7%)
GT6+	**952**	0	1	0	1	2	886 (93%)	0	3	59 (6%)
DC	**503**	0	0	0	0	1	1	434 (86%)	1	66 (13%)
NP	**17,734**	1	2	0	4	3	3	0	15,134 (85%)	2,587 (15%)
new	151	6 (4%)	6 (4%)	8 (5%)	1 (1%)	5 (3%)	7 (5%)	7 (5%)	111 (73%)	
	total (column)	**917**	**1,118**	**1,249**	**658**	**641**	**898**	**447**	**15,276**	3,244

Note: the percent in parenthesis are rounded and therefore do not necessarily need to sum to 100

Figure A1: Effects of program participation compared to non-participation (Further Vocation Training)

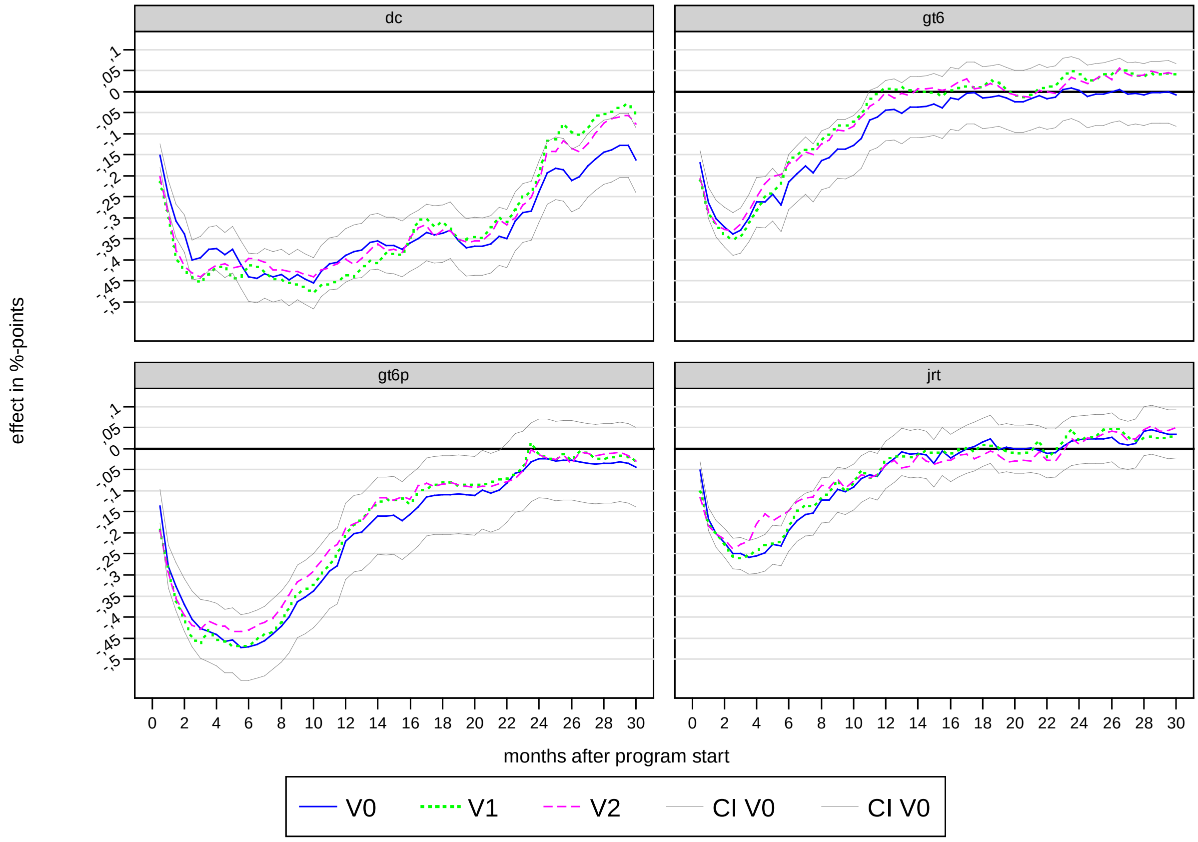


Figure A2: Effects of program participation compared to non-participation (Training Programs)

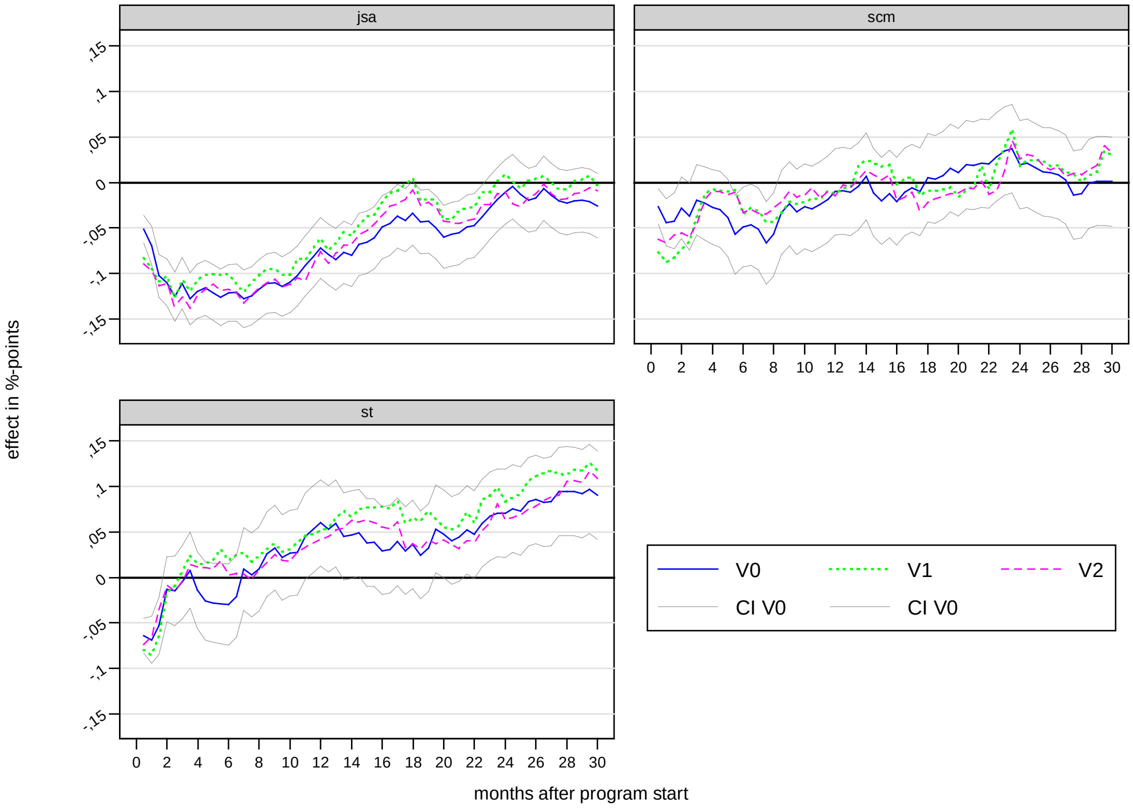


Figure A3: Differences of the ATT's (Training Programs)

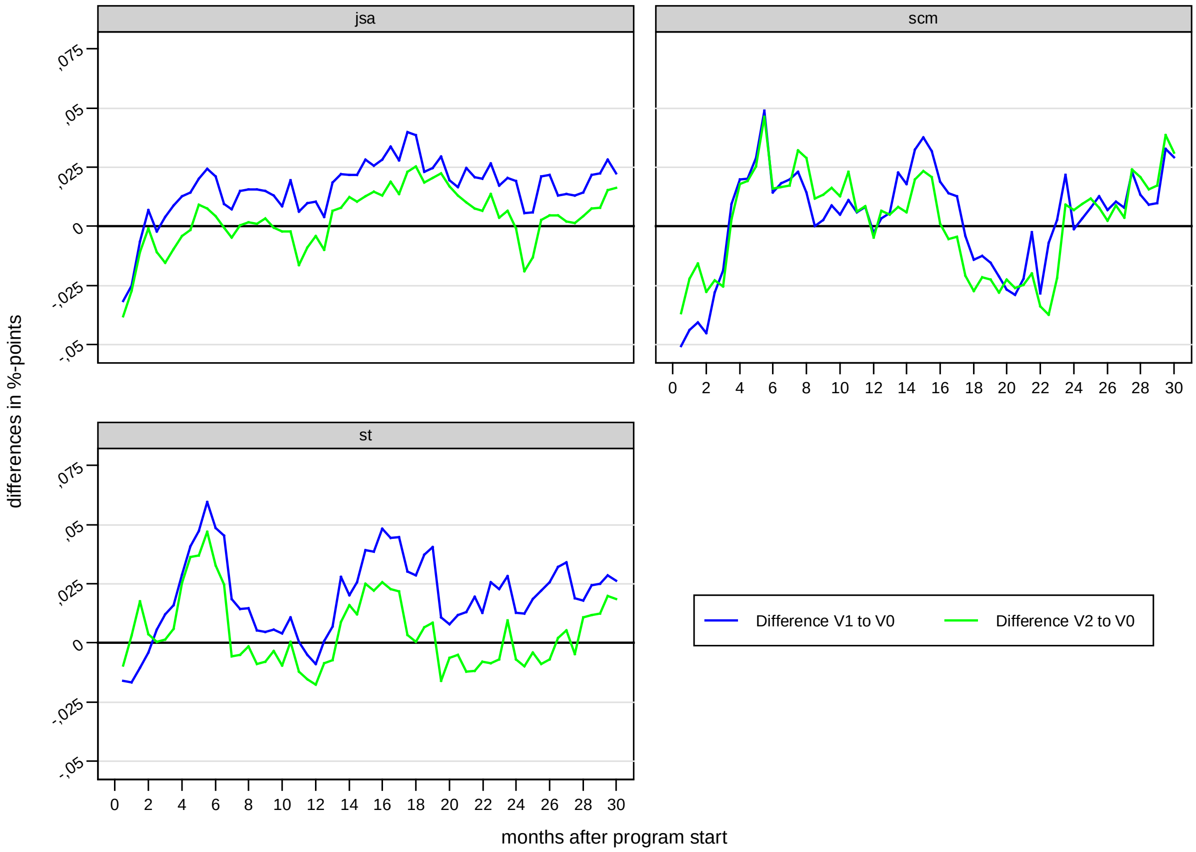


Table A3: Cumulated effects and differences (Training Programs)

model \ program	ST	SCM	JSA
V0	1.10	-0.31	-1.98
V1	1.70	-0.25	-1.49
V2	1.24	-0.28	-1.88

Imprint

FDZ-Methodenreport 4/2010

Publisher
The Research Data Centre (FDZ)
of the Federal Employment Agency
in the Institute for Employment Research
Regensburger Str. 104
D-90478 Nuremberg

Editorial staff
Stefan Bender, Britta Hübner

Technical production
Britta Hübner

Download
http://doku.iab.de/fdz/reporte/2010/MR_04-10-EN.pdf

Internet
http://fdz.iab.de/

Corresponding author:
Patrycja Scioch
The Research Data Centre (FDZ)
Regensburger Str. 104
90478 Nürnberg
Phone: 0911 / 179-4667
E-Mail: patrycja.scioch@iab.de