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Seam Effects in Longitudinal Surveys

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Seam effects are the tendency for estimates of change measured across the "seam" between two successive waves to far exceed change estimates measured within a single wave. They are present in longitudinal surveys for many behavioral variables, independently of the data collection technique or the length of the recall period. The seam problem is a quite recent issue; in survey research it has been studied mainly over the last 25 years. The first papers on this topic assessed the magnitude of seam bias and attempted to precisely measure its impact using validation data. The next efforts were directed toward understanding its possible causes. In the past few years, methods attempting to reduce seam bias have been tested and some have proven successful. Thus far, however, no strategy has been shown to completely eliminate the problem. This article summarizes the current literature on seam bias and concludes with suggestions for a future research agenda.

Key words: Seam effect; seam bias; heaping effect; dependent interviewing; calendar aided interviewing; measurement error.

1. Introduction

It is very common in longitudinal surveys to collect information at a monthly level but interview people only every four months or once a year. For example, in one wave respondents are asked about the months of the reference period in which they received social security benefits. In the next wave, typically the same questions are administered again with respect to the following reference period. The data produced contain a monthly level of detail but respondents were not interviewed each month. When the data are linked wave by wave the joint between two waves is called a seam. In computing month-to-month changes from one status to another (e.g., from receiving social security benefits to not receiving them), the transition at the joint of two waves is called a *between-wave transition*, and the transition inside each wave is called a *within-wave transition*.

A seam effect occurs when month-to-month changes in responses are much larger for the seam months than for adjacent months that are away from the seam (Rips, Conrad, and Fricker 2003; Tourangeau, Rips, and Rasinski 2000). In other words, when within-wave

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changes are less frequent than between-wave changes, we can talk about a seam effect (Kalton and Citro 1993; O'Muircheartaigh 1996). Seam effects are also referred to as "heaping effects" in some European literature (Kraus and Steiner 1998; Torelli and Trivellato 1993b).

In Figure 1, month-to-month changes in status were computed for each pair of months. The plot shows month-to-month changes from not receiving Medicaid to receiving it (No to Yes). Data come from the U.S. Census Bureau Survey of Income and Program Participation (SIPP), where respondents are interviewed every four months.[2] Information for months one to four comes from the first interview, information for months five to eight from the second interview, and information for months nine to twelve from the third interview. Since the SIPP wave length is four months, the seam between three waves occurs from the 4th to the 5th month and from the 8th to the 9th month. The first transition (1st to 2nd month) is used as a baseline with an index of 100. It should be noted that in the seam junctions the transition rates are almost eight times higher than the average within wave transitions.

Seam bias is quite a recent issue in the survey research literature. The problem was first noticed by Czajka (1983) in a reanalysis of the linked first and second wave data of the Income and Survey Development Program (ISDP)[3] (Ycas and Liniger 1981) used in a previous study by Lepkowski and Kalton (1981). Czajka noticed that the month-to-month change in the receipt of income from specific sources was more pronounced between the two waves than within waves. The following year Moore and Kasprzyk (1984) did the first seam effect analysis of the ISDP panel and found seam effects for a number of variables. The term "seam" was introduced by Burkhead and Coder (1985, p. 353) in their analysis of the 1983–84 Survey of Income and Program Participation (SIPP) data. As early as 1989 Hujer and Schneider (1989), analyzing the German Socio Economic Panel (GSOEP), which collects data annually, noted that "we find an overproportionate number of [labor force] transitions from December to January [seam], which has no real background" (p. 535).

Since the "discovery" of the seam effect, researchers have been trying to find its causes and to reduce it in two main ways: through post-hoc statistical adjustments and through developing data collection methods. In this article, a systematic review of seam effect explanations and best data collection practices to reduce this bias is provided. For a review of post-data collection statistical methods to reduce seam effects, the interested reader is referred to Lynn et al. (2005). Another goal of this article is to provide a guide to the literature of seam effects, which for the most part, is a "grey" literature found in conference proceedings, working papers, and conference presentations. Until 1991, seam effect papers were found in conference proceedings only, specifically in those of the American Statistical Association. It was in that year that the first peer reviewed paper using the term "seam effect" was published (Kalton and Miller 1991). The majority of survey research textbooks do not discuss the seam bias. Exceptions are Biemer and Lyberg (2003), Lavrakas (2008), and Tourangeau, Rips, and Rasinski (2000). Additional literature on seam effects is to be found in economics journals, specifically in articles dealing with labor force transitions.

[2] http://www.census.gov/sipp/
[3] The ISDP is the SIPP precursor.

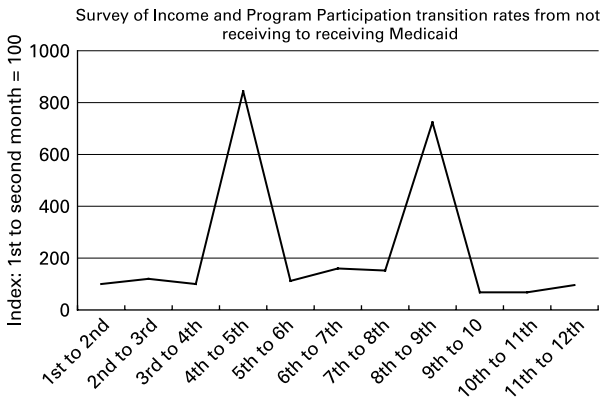

Fig. 1. 1983–84 Survey of Income and Program Participation month-to-month transition rates. Data from Burkhead and Coder (1985, p. 356)

In the next sections the effect of seam bias on data quality and findings from record check studies will be discussed to illustrate the seam bias problem and how seam and off-seam values differ from the "true values." Then the current explanations of the seam effect and the factors affecting the magnitude of seam bias are presented. The review will describe current data collection methods used to reduce seam effects. The article will end with a discussion and a research agenda. In Appendix A, a road map of seam effect studies organized by survey topic will be presented to give the reader a list of references to consult when dealing with seam effects.

2. Effect of the Seam Bias on Data Quality

Seam effects are a problem in the attempt to compute accurate survey estimates. It is sufficient to read a few papers to realize that the magnitude of seam effects is large enough to be considered a problem and not a minor source of noise in the data distribution (Willis 2001). The amount of bias between seam and off-seam data varies greatly among variables and among panels.

2.1. Universal Findings of Seam Effects in Different Panels

An interesting characteristic of seam bias is that it appears to affect almost every longitudinal study in the world. The best example is the case of labor force transitions studied in labor force surveys (LFS). The first application of seam effect analysis to labor force transitions was done by Martini (1989) using SIPP data from 1984 and 1985. In order to study labor market dynamics, individuals were coded into one of three mutually exclusive states for each month: employed (E), unemployed (U), and not in the labor force (N). The combination of states results in nine pairs of codes as shown in Table 1.

In the LFS literature, the transitions on the diagonal (EE, UU, NN) are referred to as "stayers" (stay rate) or "nonmovers." These individuals keep the same status from one month to the next. The remaining six transitions are referred to as "movers." Martini

Table 1. Possible Combinations of Mutually Exclusive States in Labor Force Status

		Month $t+1$		
		E	U	N
Month t	E	EE	EU	EN
	U	UE	UU	UN
	N	NE	NU	NN

noticed a substantial increase in transition rates for the movers at the seam for each of the six transitions, as shown in Figure 2.

Very similar findings are common to other panels: the SIPP (Gottschalk and Nielsen 2006; Martini and Ryscavage 1991; Ryscavage 2008), the Panel Study of Income Dynamics (PSID) (Callegaro 2008), and the Canadian Labor Market Activity Survey (Cotton and Giles 1998; Lemaître 1992). Torelli and Trivellato (1993a; 1993b) showed large seam effects for unemployment duration spells in the Italian Labor Force Survey. Heaping effects for inflow and outflow[4] transitions were found by Kraus and Steiner (1998) in the German Socio-Economic Panel (GSOEP). Still in the European context, seam effects in transition rates are shown in the UK subsample of the European Community Household Panel (ECHP) by Jäckle and Lynn (2007). Fisher et al. (2002) reported seam effects for labor force status changes in the 14 countries of the ECHP.

2.2. *Record Check Studies*

The problem in judging the magnitude of seam effects is that the comparison of seam to off-seam values does not provide much insight into the "true value" or the distribution of that variable. Record check studies are useful because they provide information about the distances of the seam and nonseam estimates from the "true value."

Marquis and Moore (1989) conducted a record check study for the first two SIPP interviews of 1983 and 1984. The variables selected were participation in seven U.S. federal assistance programs.[5] Administrative records from four different states were matched with the reports from the SIPP interviews conducted in 1983 and 1984. The authors computed a measure of response bias that is the sum of the differences between the respondents' reports and the administrative records (true value). When focusing on program participation the average transition bias (from receiving to not receiving and vice-versa) across seven programs was negative for the off-seam (or within-wave) months, -38%, and positive for the on-seam months with an average of $+802\%$. In other words, the seam effect was the result of too many transitions measured at the seam (overreporting) and too few measured elsewhere (underreporting). Similar results were obtained some years later in the SIPP Cognitive Research Evaluation experiment (Moore, Marquis, and Bogen 1996). A small-scale two-wave panel was created with the same design as the SIPP and

[4] Inflow is generally defined as the sum of UE and NE, while outflow is defined as the sum of EU and EN.
[5] More specifically: Aid to Families with Dependent Children, Food Stamps, Supplemental Social Security, Unemployment Insurance, Workers' Compensation, Civil Service Retirement, Social Security, and Veteran Benefits.

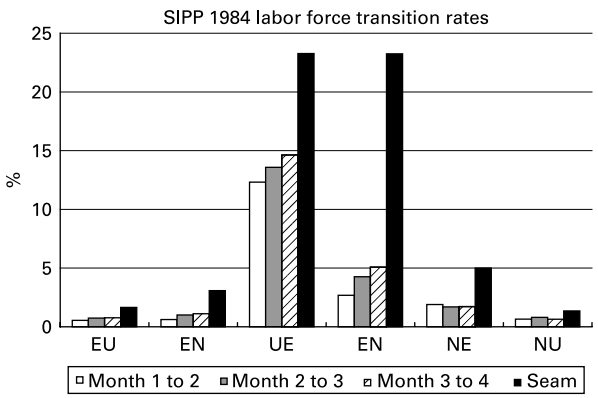

Fig. 2. Labor Force Transition Rates for the SIPP. Data from Martini (1989, p. 390)

interviews were conducted in 1992 and 1993. The experiment was conducted similarly to Marquis and Moore's, again using validation data, with a focus on four U.S. federal assistance programs.[6] The experiment involved two groups: an experimental group in which the respondents were encouraged to use records to check their answers and a control group. The average seam bias across the four programs for the control group was +43% (overreporting) while the within-wave bias was −40% (underreporting), thus providing further evidence of seam bias when interviewing without any special mnemonic aids. In the experimental group the within-wave bias was +3%, thus showing that encouraging respondents to use record checks successfully reduced underreporting. Unfortunately the seam bias was larger than that of the control group (+106%). The authors point out that "the apparent failure of the experimental procedures to produce better estimates of participation transitions at the seam . . . remains a mystery" (p. 44).

3. Explanations of Seam Effects

There are several possible factors that are believed to cause the seam effect phenomena. They can be classified into five categories: data processing, coder inconsistencies, respondent errors, satisficing, and memory issues. These five classes of causes frequently occur together and the contribution of each one depends on the kind of autobiographical event that is being studied. They have an effect on the types of error that can occur during the interview: omission of events (underreporting) and misclassification. The final effects on the estimates are within-wave "constant wave response" and spurious transitions. This conceptual model explaining the seam effect is summarized in Table 2.

3.1. Data Processing

Burkhead and Coder (1985) identify data keying error as a possible source of seam effects in the SIPP panel. Mismatches when linking two waves and edit issues as sources of

[6] Aid to Families with Dependent Children, Food Stamps, Supplemental Social Security, and Unemployment Insurance.

Table 2. Conceptual Model Explaining Seam Effects

Causes of error		Types of error		Effect on estimates
Data processing Coders' inconsistencies Respondent errors Satisficing Memory issues	⇒	Omission Misclassification	⇒	Constant wave response Spurious transitions

possible seam effect are hypothesized by Moore and Kasprzyk (1984) and by Cotton and Giles (1998). Furthermore, it is possible that procedures for assigning values for missing survey responses (imputation strategies) are contributing to seam effect patterns (Lynn et al. 2005) although no empirical research data evidence is presented by the authors.

Data processing errors do not appear to be strong contributions to the seam effect and can be easily resolved with careful data analysis.

3.2. Coders' Inconsistencies

Work done on Waves 1 and 2 of the British Household Panel Survey (BHPS) (Halpin 1998) showed that 32% of respondents who were employees in both waves, and had not changed their jobs, changed their 3-digit Standard Occupation Classification (SOC) code, and almost 18% changed their SOC major group. An analysis of a sample of the original paper questionnaire revealed that the bulk of cases were caused by either different coding of what was essentially the same job description, or different descriptions of the same job. Similar results were reported by Kalton, McMillen, and Kasprzyk (1986) and by Lynn and Sala (2006), finding changes in occupation and industry codes for respondents who had not changed jobs. As with data processing, coder inconsistencies can be decreased by employing the same coder for both waves and by improving the coder training.

3.3. Respondent Errors

Seam effects can be the result of respondents' reporting erroneous information that leads to the misclassification of a spell (Martini 1989; Martini and Ryscavage 1991). For example, a period of layoff can be reported as a period of unpaid vacation. For each misclassified spell, two transitions are recorded incorrectly. Martini and Ryscavage (1991) also make a distinction between the following situations: the "true" spell is completely contained in the reference period, and the "true" spell spans two or more reference periods but only the portion in one reference period is misclassified. In the first case (second row of Table 3) no seam effect occurs because of the misclassification, but in the second case (third row of Table 3) the misclassification contributes to the seam effect.

Respondent errors are more difficult to resolve than data processing errors and coder errors. One would expect that careful questionnaire design and pretests should minimize interpretation problems, thus leading respondents to commit fewer errors when answering questions. However, the SIPP experience in improving the questionnaires does not point in this direction.

Table 3. Illustration of Martini and Ryscavage (1991) Misclassification Spells Combinations

Months	1	2	3	4	5	6	7	8
True spells	X	O	O	X	X	X	X	X
Reported spells	*X*	*O*	*X*	*X*	*X*	*X*	*X*	*X*
True spells	X	O	O	X	X	X	X	X
Reported spells	*X*	*O*	*O*	*O*	*X*	*X*	*X*	*X*
	1st interview				2nd interview			

Note: X means presence of a status, for instance being employed, and O means presence of another status, such as being unemployed.

3.4. Forms of Satisficing

Burkhead and Coder (1985) talk about respondents purposely reporting no change in order to shorten the interview. The same idea is discussed by Martini (1988), who debates the possibility of respondents omitting details that could lead to further questioning. Young (1989) and Martini (1989) introduce the term "constant wave response" to define the case of respondents who give an answer for earlier months in an interview period identical to the answer which they give for the other months that are asked about within the same interview. Young (1989) found constant wave response effects for both continuous and categorical variables. Czajka (1999) defines the same phenomenon in different terms and talks about respondents treating the entire reference period as if it were a single observation period. Kalton and Miller (1991) discuss the possibility that respondents repeat the same answer because it simply requires less effort. All these findings are now called within-wave underreporting (Biemer and Lyberg 2003; p. 139), and from the theoretical explanations that have been proposed, it follows that it would fall under the concept of satisficing (Krosnick, Narayan, and Smith 1996).

Constant wave response has its counterpart in autobiographical memory literature. A similar phenomenon is called retrospective bias (Ross 1989), which hypothesizes that our memory of earlier periods of our lives lacks details. In order to reconstruct them, we may extrapolate current characteristics and apply them to the past. If we do not expect a characteristic to change much, we may infer that its value is identical to the present one. On the other hand, if we expect that a characteristic has changed quite a lot, we may exaggerate the difference between the past and the present. In the survey panel case, respondents may use their current status (easier to remember) to estimate earlier values, but fail to adjust for changes in the more remote portions of the reference period.

3.5. Memory Issues

With respect to memory issues, many authors have identified a number of causes that can lead to seam effects. In fact, another way of thinking about seam effects is to view them as the contrast between memory of the most recent portion of the response period of the earlier wave, and memory of the most remote portion of the response period of the later wave. The latter is likely to be an estimate rather than a direct recall (Rips, Conrad, and Fricker 2003). Figure 3 exemplifies this concept.

Forgetting a change leads to giving the same answer for each month (Kalton and Miller 1991), and this underreporting might generate spurious transitions. For example, if food stamp recipients report accurately that they received food stamps at Wave T and neglect to report them at Wave $T + 1$, a spurious transition is generated (Young 1989, p. 395). Rips, Conrad, and Fricker (2003) observe simply that recall accuracy decreases over time. This loss of recall accuracy leads to underreporting of remote changes in the reference period, thus generating spurious changes across the seam. The best evidence of this concept comes from Kalton and Miller (1991), who analyzed the Social Security benefits in the SIPP. Taking advantage of the SIPP design that rotates the groups of respondents being interviewed at different points in time, the authors showed evidence to support the memory decay hypothesis. Misplacement of events can also lead to an inflation of between-wave transitions. For example, respondents can forward-telescope an event or backward/reverse-telescope an event. More specifically, there is some evidence (Kalton and Miller 1991) that some events are reverse telescoped back to the beginning of the reference period, thus resulting in a seam effect (Martini and Ryscavage 1991).

3.6. Summary of Explanation of Seam Effects

Looking at the conceptual model explaining seam effects, the common denominator of the five types of causes is measurement error. Measurement errors are not specific to longitudinal surveys, but their visibility as seam effects is (Lynn 2005; p. 37). In looking for status changes generally from one month to the next, the transition computed between two waves suffers from the measurement error of the first wave plus the measurement error of the second wave (O'Muircheartaigh 1996), thus showing the typical pattern of a seam effect.

There is no single study that has been able to measure the specific contribution of each cause to seam effects. A further complication comes from the fact that the magnitude of seam effects is different for different variables (Young 1989). For example, classification errors are more likely to happen for variables such as job description (coder inconsistencies) or job status (respondent error). Other variables such as receiving Social Security Income ("yes"/"no" answer) are not associated with any coder error.

The reader might wonder what the major causes of seam effect are. One study was able to control for and measure the mentioned five causes of error. In a laboratory experiment

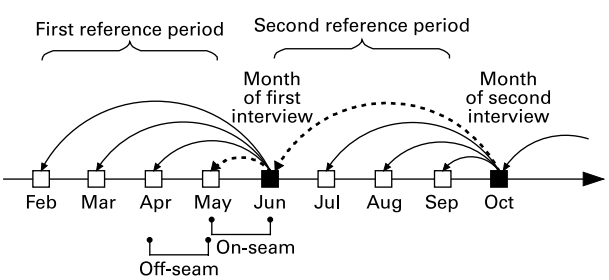

Fig. 3. Simplified interview schedule for a hypothetical panel with a reference period of four months. Modified from Tourangeau, Rips, and Rasinski (2000, p. 122)

Rips and colleagues (2003) were able to reproduce seam effect in a controlled environment. Respondents were interviewed weekly via mail for either six or eight weeks regarding topics of common life behaviors.[7] They also visited the laboratory in the middle and at the end of the study where they were questioned about the same topic. In this way the two visits to the laboratory reproduced the first and the second wave of a panel while the weekly mail questionnaires provided the validation data with which to compare the laboratory responses and measure accuracy. This ingenious design was able to provide data to disentangle and measure the relative magnitude of the causes of seam effect. The authors conclude that the seam effect was caused by a combination of memory issues and constant wave responding (Rips, Conrad, and Fricker 2003). The study used categorical ("yes" and "no") responses measuring transitions from "yes" to "no" and from "no" to "yes". In a study with a very similar design, this time with quantitative variables (amount of dollars spent on grocery items), similar results were obtained i.e., strong constant wave response strategies and recall errors (Rips et al. 2001).

4. Factors Affecting the Magnitude of Seam Effects

Different factors affect the magnitude of seam effects. The factors can be classified into three categories: respondent characteristics, spell characteristics, and length of the reference period.

4.1. Respondent Characteristics

4.1.1. Self Versus Proxy Answers

There are mixed findings in the studies of self-reported answers versus proxy answers for seam effects. The key to reaching a consensus lies in the kind of variables analyzed and, most importantly, the relation between the variables of interest and the respondent selection – self vs. proxy (Vick and Weidman 1989). When studying employment status, for example, if a proxy respondent is interviewed because the reference person is working (and thus less available for interview), a self-selection problem is created. Self-selection is one of the methodological shortcomings of much of the research which aims to address the self/proxy issue (Moore 1988). Moore and Kasprzyk (1984) found a doubling of transition rates at the seam when respondents switched from self to proxy for variables such as income type (wage and salary and self-employment status). They did not find similar effects for other variables such as Social Security benefits or Aid to Families with Dependent Children (AFDC). A possible explanation is that the recipiency of Social Security benefits and food stamps is common knowledge in the household, much more than the precise transitions of the respondent in his/her job status. Vick and Weidman (1989) do not find evidence to suggest that the use of proxy respondents increases the number of transitions at the seam. Similar results come from

[7] Examples include taking a day off from work, making a phone call to a friend or co-worker, agreeing to go on a business trip, contacting an agent to go on a business trip, purchasing tickets for a business trip, and purchasing something at a hardware store.

the Canadian LMAS panel (Murray et al. 1991). Callegaro and Belli (2007) studied the contribution of self/proxy (spouse or partner) responses to the magnitude of transitions at the seam for labor force status changes in the PSID focusing on two waves with data collected for a two year reference period.[8] When controlling for respondent age, education, sex, race, complex labor force history, poverty level, interview lag, and having the same interviewer at both waves, the combination proxy–proxy report vs. self–self report at the seam was not found to be statistically significant. A limitation of the study was that the authors did not have validation data to distinguish "real" transitions from spurious ones at the seam. The study only provides evidence that, when controlling for other factors, self/proxy answers do not increase nor decrease the chances of reporting a transition at the seam.

In summary, a proxy respondent is not necessarily less knowledgeable than the reference person, depending on the topic and how frequently it is discussed by the proxy and the other members of the household (Sudman, Bradburn, and Schwarz 1996).

4.1.2. Demographic Variables

Some respondents' demographic variables were found to amplify inconsistencies in between-wave reports even though few studies are available. One reason for the lack of studies that can identify the contribution of independent variables to seam effect in a regression type model, for example, is that there is a lack of validation data. Without validation data, it is not possible to distinguish a true transition from a spurious one. In other words, in a regular panel dataset there is no variable at the individual level indicating a true or a spurious transition. An exception is the study by Hill (1987), who, taking advantage of reinterview data, was able to create a variable at the individual level where consistent reports were treated as true transitions and inconsistent reports, were treated as spurious transitions. Consistent reports were defined when the answer about employment, unemployment, and not in the labor force for the months of December 1983 and January 1984 were the same in the first and second interview done one year later (test-retest design). Hill was then able to create a multinomial logistic model with race, age, sex, education, income, and months with the current employer as independent variables. For the dependent variable, employment status, race (whether African American), age (older respondents) and months with the current employer (less months, more inconsistencies) were found to amplify inconsistencies, thus generating spurious transitions at the seam. Jäckle and Lynn (2004) found that older people were more likely than others to provide erroneous reports or missing data, thus generating spurious transitions between waves. In the study by Callegaro and Belli (2007) the predictors of a decrease of seam effect for labor force status were age (when older), education (when higher education), sex (when male), and, most importantly, a complicated job history[9] and being below the poverty level, controlling for everything else.

[8] PSID used to collect data on a yearly basis until 1997, the year in which the data collection was shifted to every two years.

[9] Measured by counting the number of job status changes in the year preceding the interview.

4.2. Variables Showing Small Seam Bias

Some variables seem to be less prone to seam effect. In the cited study by Moore and Kasprzyk (1984) recipiency of educational benefits and basic education opportunity grants[10] showed no seam effect. In a more recent study (Moore et al. 2009) the variable school enrollment showed hardly any seam effect. A plausible explanation is that those events fall perfectly into calendar months and are easier to remember (e.g., school enrollment is a periodic event that happens every year at the same time), thus reducing the seam effect between the waves.

4.3. Length of the Reference Period

The length of the reference period increases the magnitude of seam effects. Memory decay and forgetting play a role, especially as the reference period increases. Hill (1987) studied the magnitude of seam effects for variables such as unemployment compensation and food stamp recipiency in the SIPP (data collection three times a year) and in the Panel Study of Income Dynamics (PSID) (yearly data collection). Taking advantage of the fact that the two studies overlapped for some months and had very similar question wording, Hill showed that the degree of seam effect was higher for the PSID than for the SIPP. Callegaro (2008) studied changes in the magnitude of seam effects for labor force transitions in seven waves of the PSID from 1995 to 2005. PSID used to collect data every year until 1997, when the data collection was switched to every two years. The lengthening of the recall period increased the magnitude of the changes at the seam. Comparing the 1996–97 seam (two-year recall) with the previous seam 1995–96 (one-year recall) inflow increased by 50% and outflow increased by 35%.

4.4. Questionnaire Design

Questionnaire design can also generate seam bias. In analyzing labor force transitions in the PSID, Callegaro (2008) noted the presence of seam effects within a wave. The so called *within-wave seam effect* occurred in two waves: the waves with data collected in 1999 and in 2001. In those waves the reference period was two years but the questionnaire first asked detailed questions about job history for the first reference year (in 1999 regarding 1998 – also called time *T*-1) and much later for the second reference year (1997 – also called time *T*-2). The delay between questioning and the fact that the items for time *T*-2 were much more simplified to avoid lengthening the interview contributed most to the within-wave seam bias. When the PSID changed the questionnaire (in 2003), asking job history items together and with the same questions, the within-wave seam bias disappeared (Callegaro and Belli 2007).

[10] Grants to low-income undergraduates and certain post-baccalaureate students to promote access to post-secondary education.

5. Reduction of Seam Effects – What Works

The solutions proposed to reduce seam effect include the use of dependent interviewing, calendar aided interviewing, using the same interviewer in both waves, and manipulation of question wording.

5.1. Dependent Interviewing

With the advent of Computer Assisted Interviewing (CAI) many panels have introduced dependent interviewing as a way to reduce measurement error in general (Brown, Hale, and Michaud 1998). Dependent interviewing questions are classified as proactive and reactive (Brown, Hale, and Michaud 1998; Mathiowetz and McGonagle 2000). In proactive dependent interviewing the respondents are asked questions they did not answer in the previous wave, or reminded of previous responses. In the latter case the previous information can be used to aid the respondent's memory and provide a bounded recall before providing a standard independent question. This strategy is called *remind-continue*. Another strategy, called *remind-confirm*, is to ask the respondent to check and confirm previously recorded data. One more option is to ask the respondent if there are any changes since the last wave (*remind-still*)[11] (Jäckle 2009).

With reactive dependent interviewing the information fed forward is used to carry out edit checks during the interview. Reactive dependent interviewing is used as a form of follow-up probe for a nonresponse item (e.g., don't know, don't remember) or to check the consistency with a previous report. In the first case, *item nonresponse follow-up*, for example, if the respondent does not provide an answer to the income question, he/she is provided with the previous report, asking if that value "sounds about right" (Moore et al. 2004). In the second case, *corrective follow-up*, consistency checks on a specific question can be prompted for everyone (e.g., to check a verbatim answer to a previous report). This is done to clarify reports that are inconsistent with previous ones, or to selectively prompt only if the current report differs by more than a certain threshold from the previous report[12] (Jäckle 2009).

Few studies tested the effectiveness of dependent interviewing in reducing seam effect. In the late 1990s the SIPP carried out a program studying dependent interviewing, called the SIPP methods panel project (Moore et al. 2004). After many pretests, a more sophisticated and rigorous dependent interviewing program was implemented on a full scale in 2004 (Moore et al. 2009). In comparisons of the seam bias of the 2004 waves with that of previous waves where dependent interviewing was not used, specifically the 2001 waves, 42 of 45 comparisons showed a statistically significant difference. As a way to

[11] Examples: *Remind-continue* "According to our records, when we last interviewed you, on < Interview date >, you were receiving < Income source >, either yourself or jointly. For which months since < Interview month > have you received < Income source > ?" *Remind-confirm* "When we last interviewed you, on < Interview date >, our records show that you were < Labor market activity >. Is that correct?" *Remind-still* "Last time we interviewed you, on < Interview date >, you said your occupation was < Occupation >. Are you still in that same occupation?".

[12] Examples: *item nonresponse follow-up* ". . .last time you received <$$$> in food stamps. Does that still sound about right?" *Corrective follow-up* "Can I just check, according to our records you have in the past received < Income source >. Have you received < Income source > at any time since < Interview date > ?"

summarize the results, the authors computed a change rate ratio. The change rate ratio is the number of transitions at the seam divided by the average number of month-to-month transitions within the wave (seam/average of within-waves transitions). In the absence of any seam bias this ratio should be close to 1. For variables of "need-based" public assistance type (receipt of federal Supplemental Survey Income, AFDC, food stamps, and three other variables) the 2001 average ratio was 18.2, compared to 7.2 from 2004 when dependent interviewing was used. For nonneed-based income sources and characteristic variables (private heath insurance coverage, private pensions, Medicare and eight other variables) the 2001 average ratio was 22, compared to 7 from 2004 when dependent interviewing was used (calculated from the original tables). Dependent interviewing not only reduced the change at the seam but also increased the change off-seam (Moore et al. 2008). This is a very important result corroborating the previous SIPP finding from validation data that off-seam estimates are generally underestimates of the observable facts (Marquis and Moore 1989; Marquis, Moore, and Bogen 1991).

An experiment collecting work history data involving independent interviewing as well as proactive and reactive dependent interviewing was carried out on a subsample of the UK part of the European Community Household Panel (EHCP) (Jäckle and Lynn 2007). Independent and reactive dependent interview data were combined. The proactive dependent interviewing clearly reduced seam effects. For example, transition rates (at the seam) for occupational status were reduced from 32% to 9% in the proactive dependent interviewing group. The authors also maintain that proactive dependent interviewing did not lead to underreporting of change since in the off-seam months the average monthly transition rate was 2% for all treatment groups. This study is one of the most successful at reducing seam bias.

Implementing dependent interviewing, however, poses some challenges. The first one is careful and elaborate software programming, making sure that the right information is fed to the right respondent. This adds extra programming time, testing time, and overall cost (Hoogendoorn 2004). Secondly, question wording and ethical issues arise when there is a switch from self to proxy and vice versa. When information is collected from one respondent and fed to another respondent, question wording can become awkward. In order to avoid complicated[13] verbiage such as "he/she told us," "your wife/husband reported. . ." one strategy is to use sentences such as: "according to our records, when we last interviewed you. . ." Moreover, ethical issues and confidentiality of the answers are at stake when dependent interviewing is used to feed information to a respondent different from that of the previous wave. One solution adopted by the U.S. Census Bureau, for example, is to ask permission to disclose the respondent's answers to other household members[14] (Chan and Moore 2006; Pascale and Mayer 2004). Dependent interviewing, even with these challenges and the extra programming required to implement it, is currently viewed as an effective method in reducing seam bias in many different panels with different collection strategies.

[13] This is complicated also from a software programming point of view.

[14] For example, the SIPP uses the following formulation: "One last thing. . . We recontact households once over a 4-month period to update information. If we talk to someone else in your household next time, instead of you, is it OK if we use your answers as a starting point?" (Chan and Moore 2006; p. 22).

5.2. *Calendar-aided Interviewing*

Calendar-aided interviewing is a set of data collection strategies based on a calendar that is used as a reference and anchor point. The calendar does not necessarily have to be shown to the respondent, in fact calendar-based interviewing can be applied in telephone interviews. Examples of calendar-based interviewing are timeline studies, event history calendar and diary studies (Belli, Stafford, and Alwin in press). In this review the first two applications will be discussed because they are related to studies on seam effect.

5.2.1. Timelines

A 32-month calendar was used as an aid for SIPP respondents in the Chicago region (Kominski 1990). After completion of the first face-to-face interview (Wave 1), the interviewers filled out (in their own homes) the calendar with the information obtained from the standardized questionnaire. In the second interview (Wave 2) the interviewers handed the appropriate calendar to the respondents prior to the start of the interview. During the interview the respondents were able to look at the calendar and the events recorded on it. At the conclusion of Wave 2, the interviewers updated the calendar that would be used again in Wave 3. Results from the analysis comparing the ratio of average monthly seam to off-seam transitions with previous SIPP data showed a reduction of the seam transitions for almost all variables analyzed. Furthermore, examination of the calendar showed that there were numerous instances where the calendar facilitated longitudinal editing and correction of data (Kominski 1990).

The Household, Income and Labour Dynamics in Australia (HILDA) panel uses timelines for collecting data on schooling and employment history during their face-to-face interviews. The panel collects data on a yearly basis but for schooling and employment history the reference period overlaps by six months. In other words the timeline shown to respondents is 18 months long (from July to December of the next year) thus collecting information regarding the months from July to December twice. Carroll (2006) studied seam effects for Waves 1 and 2 of the HILDA for inflow and outflow from unemployment showing transition rates five times higher at the seam when compared to the within-wave transitions. However, the study is not experimental in nature and we do not know if without the calendar the seam bias would have been larger. The overlapping wave design enabled the author to measure consistency between answers from the first wave to the second wave for the months of July to December. The results show that "27% of people gave answers that were never consistent (where the categories are unemployment and not employment), 40% of people were consistent the entire time and the remaining were consistent in between one to eight of the nine periods examined" (Carroll 2006; p. 301).

5.2.2. Event History Calendar

Callegaro and Belli (2007) studied changes in seam effect of the 1995–2005 waves of the PSID. A substantial part of the PSID questionnaire was administered with the Event History Calendar (EHC) in the last two waves (2003 and 2005). An EHC interview is centered around a customized calendar that shows the reference period under investigation (Axinn, Pearce, and Ghimire 1999; Belli and Callegaro in press). The calendar contains timelines for work history, residence history, household composition and other domains

relevant to the topic of the study. The interviewer guides the respondent in answering queries for each timeline, starting with the first domain and continuing down until the last domains, which are the focal points of the study, are completed. The EHC also allows moving back and forth among the domains. The process uses information and dates for each completed domain to help the respondent correctly place other events in the appropriate time-frame. When compared to conventional questionnaire (CQ) data collection, EHC has been shown to reduce underreporting and improve the accuracy of the recall in the timeline (Belli, Shay, and Stafford 2001; Belli et al. 2007). Based on these findings, Callegaro and Belli (2007) compared the magnitude of the effect at each seam of the waves collected with conventional questionnaires for labor force transition rates with the magnitude of the effect at the seam of the last two waves collected with EHC. The EHC seam effect was slightly lower than in the case of the CQ. The authors explain this finding using the argument that with such a long recall period (two years) the task becomes so daunting that even EHC, thus far proving superior to CQ in terms of data quality of retrospective autobiographical behavior, is not sufficient to reduce bias further and some other more aggressive memory-aided technique might need to be used.

5.3. Keeping the Same Interviewer in Both Waves

Vick and Weidman (1989) studied seam effects in the SIPP for income recipiency. They found that having the same interviewer for consecutive waves reduced the number of reported transitions at the seam, as compared to having different interviewers. The interviews were conducted face-to-face with a paper and pencil questionnaire. A possible explanation of the above findings is that the interviewer could have acted as a sort of "dependent interviewing mechanism," possibly reminding the respondent of previous answers (four months before). The interviewer could also have facilitated the recall just through his/her presence in the household and increased consistency, disambiguating inconsistencies because of his/her previous knowledge about that interview. The main limitation of this study is that interviewers were not randomly allocated, thus making it more difficult to assess the cause of an increase of seam effect when there is a switch.

Callegaro and Belli (2007) tested the above hypothesis using a multivariate model on labor force transition for the PSID panel. When controlling for other variables, having the same interviewer in both waves did not cause any statistically significant difference in the magnitude of the seam effect. One limitation is that few interviewers conducted the interview with the same household in both waves. More research is definitely needed on this topic.

5.4. Manipulation of Question Wording

In the previously mentioned laboratory setting study by Rips, Conrad, and Fricker (2003) the researchers experimented by grouping the questions by topic or by reference period. In the first case, questions about a topic were asked referring to each week in a sequence, similar to the procedure in longitudinal studies. For example a respondent is asked questions about food stamps in the last month, and then immediately answers the same question regarding the previous two, three, and four months. This sequencing can encourage repeating the answers to one question for each subsequent reference period

(constant wave response). In the second case the questions were grouped by reference period and all topics were asked in one time period. To come back to the example, the respondent is asked about food stamps and all the other questions regarding the last month, and then again the same battery of questions for the previous two, three, and four months. The authors found that grouping questions by reference period discourages satisficing. Furthermore, when recall by reference period is coupled with backward order of retrieval (i.e., reverse chronological) it produces less constant wave response, lower seam effects and higher accuracy levels. Even though some limitations have been indicated for this study, most notably the choice of questions that do not resemble common survey items (Martin 2001; Willis 2001), the results are convincing and the study is indeed the first successful attempt to reproduce seam effects in a controlled laboratory setting.

6. Summary

Seam effects are common across many types of behavioral variables and have been found in different panels across the world. They are present even with different data collection methodologies, regardless of the length of the reference period. The problem becomes evident because of the way variables measuring transitions are constructed. Traditional descriptive statistics measuring the prevalence of a status for each month (or week) of the longitudinal dataset do not highlight seam problems. The issue shows up when for each subject month-to-month transition rates are computed. As soon as one moves from within-wave transitions to transitions at the seam, any kind of inconsistency between the two waves is picked up by the computation, thus highlighting abnormal heaping of the data. It is inescapable, however, that at the joint of two waves we have measurement errors from the first wave plus measurement errors from the second wave (Lynn 2005; O'Muircheartaigh 1996).

The common denominator of the methods that thus far have proven effective in reducing seam effects is that they use various kinds of memory aids in helping the respondent to retrieve information and discourage satisficing. Dependent interviewing, calendar-aided interviewing, the EHC, and having the same interviewer in successive waves all give respondents more retrieval cues than a conventional questionnaire. With dependent interviewing the respondents are reminded of the previous wave's answer and/or inconsistencies are pointed out, thus providing them with more information to answer the questionnaire more effectively. The calendar method used by Kominski (1990) visualizes the previous interview and works as a sort of diary, providing, in a different form, retrieval cues similar to those given in dependent interviewing. The EHC interviewing style allows the respondents to use multiple retrieval strategies at the same time, which possibly increases the precision of the recall. If the same interviewer administers the questionnaire in each wave, then the same interviewing setting is recreated, using Tulving's memory-encoding specificity principle (Tulving 1985).

Grouping the questions by reference period and not by topic (Rips, Conrad, and Fricker 2003) reduces satisficing behaviors and "forces" the respondent to think more about the events. Lastly, backward order of retrieval seems more effective than forward order of retrieval.

Among all of the above methods, only dependent interviewing has been proven successful in reducing seam bias across different studies and panels. The other methods have been applied only once or twice and thus more studies are needed to assess their effectiveness.

Two studies provide evidence that if panel designers want to increase the length of the reference period they will most likely pay the price of an increase in seam bias (Callegaro 2008; Hill 1987).

7. Suggested Research Agenda

- Seam effects have been studied on only a few groups of variables, as the reader can infer from Appendix A. Research is needed using other variables, in order to understand which ones are more sensitive to seam effect and which ones have less or no seam bias. Examples of other variables include schooling, travel, vacation or unpaid time off.
- Studies varying the length of the reference period can shed some light on the effectiveness of each data collection strategy in reducing seam bias and at what length each strategy starts becoming less effective.
- Without validation data or external data it is impossible to judge whether an increase in transition at the joint is due completely to a seam bias or due partly to the fact that the "real" transitions are higher at the seam. This is the case, for example, when it comes to LFS transitions that for many panels have the seam between December and January. Work toward this direction is the recent effort of the U.S. Bureau of Labor Statistics to provide month-to-month labor force transition rates coming from the Current Population Survey.[15]
- More studies are needed to evaluate the effectiveness of calendar-aided methods for reducing seam effect. An effort in this direction is the joint work by the PSID and the U.S. Census Bureau in reengineering the SIPP, culminating in the conference on event history calendar methods in December 2007.[16]
- The combination of more than one method to reduce seam bias should be tested. For example, EHC has never been combined with dependent interviewing and/or with the grouping of questions by topic.
- More studies with a validation data component should be conducted. Federal agencies have a special advantage in being able to pull validation data from different studies and linking these data to the respondents as, for example, in the case of the SIPP (Fields and Moore 2007).
- A panel design with overlapping reference periods such as the Household, Income and Labour Dynamics in Australia (HILDA) Survey provides an opportunity to measure seam bias. Overlapping reference periods from wave to wave are basically a test-retest procedure, because the same questions regarding the same reference period are administered at two different points in time. Inconsistencies of reports are a direct indication of seam bias.

[15] http://www.bls.gov/cps/cps_flows.htm
[16] http://psidonline.isr.umich.edu/Publications/Workshops/ehc-07papers.html

The goal of this article was to provide a solid background of studies about seam effects and identify possible data collection strategies to decrease the seam effects. The intention was to provide a reference for researchers planning to do experiments on seam effects. I also hope that my effort can serve as a starting point for the development of a theory of seam effect that can help researchers predict and control the seam bias. Efforts in this direction have already been made by Rips, Conrad, and Fricker (2003) and, more recently, by Jäckle (2008).

Appendix A. Seam Effect Studies by Survey Topic

Topic	Studies
Income recipiency/ program participation	Burkhead and Coder (1985), Hill (1987), Kalton and Miller (1991), Kominski (1990), Marquis and Moore (1989), Marquis, Moore, and Huggins (1990), Miller, Lepkowski, and Kalton (1992), Moore et al. (in press), Moore and Kasprzyk (1984), and Young (1989)
Insurance	Burkhead and Coder (1985), Congressional Budget Office (2003), and Czajka (1999)
Labor force transitions/ gross flow	Bassi (1998), Callegaro (2008), Cotton and Giles 1998, Jäckle and Lynn (2004), Lemaître (1992), Martini (1988), (1989), Martini and Ryscavage (1991), Murray et al. (1991), Ryscavage (1993) Torelli and Trivellato (1993a), and Wolff and Augustin (2003)
Unemployment	Carroll (2006), Hujer and Schneider (1989), Jürges (2005), (2007), Kraus and Steiner (1998), and Torelli and Trivellato (1993b)

8. References

Axinn, W.G., Pearce, L.D., and Ghimire, D.J. (1999). Innovations in Life History Calendar Applications. Social Science Research, 28, 243–264.

Bassi, F. (1998). Gross Flows Estimation from the Survey of Income and Program Participation. Journal of Economic and Social Measurement, 25, 97–110.

Belli, R.F. and Callegaro, M. (in press). The Emergence of Calendar Interviewing: A Theoretical and Empirical Rationale. In Calendar and Time Diary Methods in Life Course Research, R.F. Belli, F.P. Stafford and D. Alwin (eds). Newbury Park, CA: Sage.

Belli, R.F., Shay, W.L., and Stafford, F.P. (2001). Event History Calendars and Question List Surveys: A Direct Comparison of Interviewing Methods. Public Opinion Quarterly, 65, 45–74.

Belli, R.F., Smith, L.M., Andreski, P.M., and Agrawal, S. (2007). Methodological Comparison between CATI Event History Calendar and Standardized Conventional Questionnaire Instruments. Public Opinion Quarterly, 71, 603–622.

Belli, R.F., Stafford, F.P., and Alwin, D. (in press). Calendar and Time Diary Method in Life Course Research. Newbury Park, CA: Sage.

Biemer, P.P. and Lyberg, L.E. (2003). Introduction to Survey Quality. Hoboken, NJ: Wiley.

Brown, A., Hale, A., and Michaud, S. (1998). Use of Computer Assisted Interviewing in Longitudinal Surveys. In Computer Assisted Survey Information Collection, M. Couper, R.P. Baker, J. Bethlehem, C.Z.F. Clark, J. Martin, W.L. Nicholls, II, and J.M. O'Reilly (eds). New York: Wiley, 185–200.

Burkhead, D. and Coder, J. (1985). Gross Changes in Income Recipiency from the Survey of Income and Program Participation. Proceedings of the American Statistical Association, Social Statistics Section. Washington, DC, 351–356.

Callegaro, M. (2008). Changes in Seam Effects Magnitude due to Changes in Question Wording and Data Collection Strategies. An Analysis of Labor Force Transitions in the PSID. Proceedings of the 62nd Annual Conference of the American Association for Public Opinion Research [Cd-ROM], Alexandria, VA: American Statistical Association, 3933–3940.

Callegaro, M. and Belli, R.F. (2007). Impact of Event History Calendar on Seam Effect in the PSID: Lessons for SIPP. Event History Calendar Method Conference, Dec 5–6. Retrieved January 2008, from http://psidonline.isr.umich.edu/Publications/Workshops/ehc-07papers/Callegaro_Belli_EHC_Census_conference_Submission.pdf

Carroll, N.E. (2006). Explaining Unemployment Duration in Australia. Economic Record, 82, 298–314.

Chan, A.Y. and Moore, J.C. (2006). The Impact of a Confidentiality Protection Policy on the Use of Dependent Interviewing in a Longitudinal Household Panel Survey: The Case of the Survey of Income and Program Participation. Paper presented at the Conference on Methodology of Longitudinal Surveys, 12–14 July. UK: University of Essex.

Congressional Budget Office (2003). How Many People Lack Health Insurance and for How Long? Retrieved Jan 2008, from http://www.cbo.gov/showdoc.cfm?index = 4210 andsequence = 0

Cotton, C. and Giles, P. (1998). The Seam Effect in the Survey of Labour and Income Dynamics. Income and Labour Dynamics Working Paper 75f0002m. Retrieved January 2008, from http://www.statcan.ca/english/research/75F0002MIE/75F0002MIE1998018.pdf

Czajka, J.L. (1983). Subannual Income Estimation. In Technical, Conceptual, and Administrative Lessons of the Income Survey Development Program (ISDP), D.H. Martin (ed.). New York: Social Science Research Council, 87–97.

Czajka, J.L. (1999). The Seam Effect in SIPP Estimates of the Number and Duration of Spells of Uninsurance among Children. Proceedings of the American Statistical Association, Section on Government Statistics, Washington, DC, 256–261.

Fields, J. and Moore, J.C. (2007). Planning for a SIPP Calendar Validation Study: Design and Analysis Plans. The Use of Event History Calendar (EHC) Methods in Panel Surveys, December 5–6. Retrieved January 2008, from http://psidonline.isr.umich.edu/Publications/Workshops/ehc-07papers/Fields%20and%20Moore%20EHC-11-26-2007.pdf

Fisher, K., Fouarge, D., Muffels, R., and Verma, V. (2002). Examining Flexible Labour in Europe – the First Three Waves of the ECHP. In Social Science Methodology in the

New Millennium: Updated and Extended Proceedings of the Fifth International Conference on Logic and Methodology Held at Cologne, Germany, October 3–6, 2000 (Cd-ROM), J. Hox, E. De Leeuw, P. Schmidt and J. Blasius (eds), Leverkusen: Leske and Budrich.

Gottschalck, A.O. and Nielsen, R.B. (2006). The Presence of the Seam in SIPP Panels: Effects on Labor Force Estimates. Paper presented at the Eastern Economic Association Annual Conference, February 23–26. Philadelphia, PA.

Halpin, B. (1998). Unified BHPS Work-Life Histories: Combining Multiple Sources into a User-Friendly Format. Bulletin de Méthodologie Sociologique, 60, 34–79.

Hill, D.H. (1987). Response Errors around the Seam: Analysis of Change in a Panel with Overlapping Reference Periods. Proceedings of the American Statistical Association, Section on Survey Research Methods. Washington, DC, 210–215.

Hoogendoorn, A.W. (2004). A Questionnaire Design for Dependent Interviewing that Addresses the Problem of Cognitive Satisficing. Journal of Official Statistics, 20, 219–232.

Hujer, R. and Schneider, H. (1989). The Analysis of Labor Market Mobility Using Panel Data. European Economic Review, 33, 530–536.

Jäckle, A. (2008). The Causes of Seam Effects in Panel Surveys. Working Papers of the Institute for Social and Economic Research, Paper 2008–14. Retrieved April 2008, from http://www.iser.essex.ac.uk/pubs/workpaps/pdf/2008-14.pdf

Jäckle, A. (2009). Dependent Interviewing: A Framework and Application to Current Research. In Methodology of Longitudinal Surveys, P. Lynn (ed.), Hoboken, NJ: Wiley.

Jäckle, A. and Lynn, P. (2004). Dependent Interviewing and Seam Effects in Work History Data. Working Papers of the Institute for Social and Economic Research, Paper 2004–24. Retrieved January 2008, from http://www.iser.essex.ac.uk/pubs/workpaps/pdf/2004-24.pdf

Jäckle, A. and Lynn, P. (2007). Dependent Interviewing and Seam Effects in Work History Data. Journal of Official Statistics, 23, 521–551.

Jürges, H. (2005). Retrospective Error in SOEP Calendar Data: The Case of Unemployment. Journal of Applied Social Science Studies (Schmollers Jahrbuch), 125, 157–165.

Jürges, H. (2007). Unemployment, Life Satisfaction and Retrospective Error. Journal of the Royal Statistical Society, Series A, 170, 43–61.

Kalton, G. and Citro, C.F. (1993). Panel Surveys: Adding the Fourth Dimension. Survey Methodology, 19, 205–215.

Kalton, G., McMillen, D.B., and Kasprzyk, D. (1986). Nonsampling Error Issues in the SIPP. SIPP Working Paper No. 10. Washington, DC: U.S. Bureau of Census.

Kalton, G. and Miller, M.E. (1991). The Seam Effect with Social Security Income in the Survey of Income and Program Participation. Journal of Official Statistics, 7, 235–245.

Kominski, R. (1990). The SIPP Event History Calendar: Aiding Respondents in the Dating of Longitudinal Events. Proceedings of the American Statistical Association, Section of Survey Research Methods. Washington, DC, 553–558.

Kraus, F. and Steiner, V. (1998). Modelling Heaping Effects in Unemployment Duration Models – with An Application to Retrospective Event Data in the German

Socio-Economic Panel. Jahrbücher für Nationalökonomie und Statistik/Journal of Economics and Statistics, 217, 550–573.

Krosnick, J.A., Narayan, S., and Smith, W.R. (1996). Satisficing in Surveys: Initial Evidence. New Directions for Evaluation. In Advances in Survey Research. M.T. Braverman and J.K. Slater (eds). San Francisco: Jossey-Bass, 70, 29–44.

Lavrakas, P.J. (ed.). (2008). Encyclopedia of Survey Research Methods. Newbury Park, CA: Sage.

Lemaître, G. (1992). Dealing with the Seam Problem for the Survey of Labour and Income Dynamics. SLID Research Paper Series No. 92–05. Retrieved January 2008, from http://www.statcan.ca/english/research/75F0002MIE/75F0002MIE1992005.pdf

Lepkowski, J. and Kalton, G. (1981). Investigations of Longitudinal Imputation Strategies for the ISDP Research Panel. Ann Arbor, MI: Survey Research Center, University of Michigan.

Lynn, P. (2005). Longitudinal Survey Methodology. Bilbao: Eustat.

Lynn, P., Buck, N., Burton, J., Jäckle, A., and Laurie, H. (2005). A Review of Methodological Research Pertinent to Longitudinal Survey Design and Data Collection. Working Papers of the Institute for Social and Economic Research, Paper 2005–29. January 2008, from http://www.iser.essex.ac.uk/pubs/workpaps/pdf/2005-29.pdf

Lynn, P. and Sala, E. (2006). Measuring Change in Employment Characteristics: The Effects of Dependent Interviewing. International Journal of Public Opinion Research, 18, 500–509.

Marquis, K.H. and Moore, J.C. (1989). Some Response Errors in SIPP – with Thoughts About Their Effects and Remedies. Proceedings of the American Statistical Association, Section of Survey Research Methods. Washington, DC, 381–386.

Marquis, K.H., Moore, J.C., and Bogen, K. (1991). A Cognitive Approach to Redesigning Measurement in the Survey of Income and Program Participation. Proceedings of the American Statistical Association, Section on Survey Research Methods. Washington, DC, 413–418.

Marquis, K.H., Moore, J.C., and Huggins, V.J. (1990). Implications of SIPP Record Check Results for Measurement Principles and Practice. Proceedings of the American Statistical Association, Section of Survey Research Methods. Washington, DC, 564–569.

Martin, E. (2001). Remarks on Rips et al. Paper: Seam Effect for Quantitative and Qualitative Facts. In Statistical Policy Working Paper 33 – Seminar on the Funding Opportunity in Survey Research, Washington, DC: Federal Committee on Statistical Methodology, 30–33.

Martini, A. (1988). Retrospective vs. Panel Data in Estimating Labor Force Gross Flows. Proceedings of the American Statistical Association, Social Statistics Section. Washington, DC, 109–114.

Martini, A. (1989). Seam Effect, Recall Bias, and the Estimation of Labor Force Transition Rates from SIPP. Proceedings of the American Statistical Association, Section on Survey Research Methods. Washington, DC, 387–392.

Martini, A. and Ryscavage, P. (1991). The Impact of Survey and Questionnaire Design on Longitudinal Labor Force Measures. Proceedings of the 1991 Annual Research Conference. Washington, DC: U.S. Bureau of the Census, 731–758.

Mathiowetz, N.A. and McGonagle, K.A. (2000). An Assessment of the Current State of Dependent Interviewing in Household Surveys. Journal of Official Statistics, 16, 401–418.

Miller, D.P., Lepkowski, J., and Kalton, G. (eds) (1992). Estimating Duration of Food Stamps Spells from the SIPP. Proceedings of the American Statistical Association, Section on Survey Research Methods. Washington, DC, 560–565.

Moore, J.C. (1988). Self/Proxy Response Status and Survey Response Quality. A Review of the Literature. Journal of Official Statistics, 4, 155–172.

Moore, J.C., Bates, N., Pascale, J., and Okon, A. (2009). Tackling Seam Bias through Questionnaire Design. In Methodology of Longitudinal Surveys, P. Lynn (ed.). Hoboken, NJ: Wiley.

Moore, J.C. and Kasprzyk, D. (1984). Month-to-Month Recipient Turnover in the ISDP. Proceedings of the American Statistical Association, Section on Survey Research Methods. Washington, DC, 726–731.

Moore, J.C., Marquis, K.H., and Bogen, K. (1996). The SIPP Cognitive Research Evaluation Experiment: Basic Results and Documentation. SIPP Working Paper No. 202. Retrieved January 2008, from http://www.sipp.census.gov/sipp/wp9601.pdf

Moore, J.C., Pascale, J., Doyle, P., Chan, A.Y., and Griffiths, J.K. (2004). Using Field Experiments to Improve Instrument Design: The SIPP Methods Panel Project. Methods for Testing and Evaluating Survey Questionnaires, S. Presser, J.M. Rothgeb, M.P. Couper, J.T. Lessler, J. Martin, and E. Singer (eds). Hoboken, NJ: Wiley, 189–207.

Murray, S.T., Michaud, S., Egan, M., and Lemaître, G. (1991). Invisible Seams: The Experience with the Canadian Labour Market Activity Survey. Proceedings of the 1991 Annual Research Conference. Washington, DC: U.S. Bureau of the Census, 715–730.

O'Muircheartaigh, C. (1996). Measurement Errors in Panel Surveys: Implications for Survey Design and for Survey Instruments. In Atti Della Xxxviii Riunione Scientifica Della Società Italiana Di Statistica, Rimini: Maggioli, 1, 207–218.

Pascale, J. and Mayer, T.S. (2004). Exploring Confidentiality Issues Related to Dependent Interviewing: Preliminary Findings. Journal of Official Statistics, 20, 357–377.

Rips, L.J., Conrad, F.G., and Fricker, S.S. (2003). Straightening the Seam Effect in Panel Surveys. Public Opinion Quarterly, 67, 522–554.

Rips, L.J., Conrad, F.G., Fricker, S.S., and Behr, J. (2001). Seam Effect for Quantitative and Qualitative Facts. In Statistical Policy Working Paper 33 – Seminar on the Funding Opportunity in Survey Research, Washington, DC: Federal Committee on Statistical Methodology, 7–25.

Ross, M. (1989). Relation of Implicit Theories to the Construction of Personal Histories. Psychological Review, 96, 341–357.

Ryscavage, P. (1993). The Seam Effect in SIPP's Labor Force Data: Did the Recession Make it Worse? SIPP Working Paper No. 180. Retrieved Jan 2008, from http://www.sipp.census.gov/sipp/wp9308.pdf

Sudman, S., Bradburn, N.M., and Schwarz, N. (1996). Thinking About Answers. The Application of Cognitive Processes to Survey Methodology. San Francisco: Jossey Bass.

Torelli, N. and Trivellato, U. (1993a). Data Inaccuracies and Sampling Plan in a Model of Unemployment Duration. In Panel Data and Labour Dynamics, H. Bunzel, P. Jensen, and N. Westergård-Nielsen (eds). Amsterdam: North-Holland, 171–188.

Torelli, N. and Trivellato, U. (1993b). Modelling Inaccuracies in Job-Search Duration Data. Journal of Econometrics, 59, 187–211.

Tourangeau, R., Rips, L.J., and Rasinski, K. (2000). The Psychology of Survey Response. Cambridge: Cambridge University Press.

Tulving, E. (1985). Elements of Episodic Memory. Oxford: Oxford University Press.

Vick, S. and Weidman, L. (1989). Reporting of Income Recipiency by Self and Proxy Respondents in SIPP. Proceedings of the American Statistical Association, Section of Survey Research Methods. Washington, DC, 315–319.

Willis, G. (2001). Discussion on Rips et al. Paper: Seam Effect for Quantitative and Qualitative Facts. Statistical Policy Working Paper 33 – Seminar on the Funding Opportunity in Survey Research, Washington DC: Federal Committee on Statistical Methodology, 26–29.

Wolff, J. and Augustin, T. (2003). Heaping and Its Consequences for Duration Analysis. A Simulation Study. Allgemeines Statistisches Archiv, 87, 59–86.

Ycas, M.A. and Liniger, C.A. (1981). The Income Survey Development Program: Design Features and Initial Findings. Social Security Bulletin, 44, 13–19.

Young, N. (1989). Wave-Seam Effects in the SIPP. Proceedings of the American Statistical Association, Section on Survey Research Methods. Washington, DC, 393–398.

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