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Notes and debates

Déjà lu: On the limits of data reuse across multiple publications

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ABSTRACT

Scholars in our field, Operations and Supply Chain Management (OSCM), are under high pressure to show research productivity. At most schools, this productivity is measured by the number of journal articles published. One possible response to such pressure is to improve research efficiency: publishing more journal articles from each data collection effort. In other words, using one dataset for multiple publications. As long as each publication makes a sufficient contribution, and authors ensure transparency in methods and consistency across publications, generating more than one publication from one data collection effort is possible. The aim of this Notes and Debates article, however, is to draw attention to *inappropriate* reuse of empirical data in OSCM research, to explain its implications and to suggest ways in which to promote research quality and integrity. Based on two cases of extensive data reuse in OSCM, eighteen problematic practices associated with the reuse of data across multiple journal articles are identified. Recommendations on this issue of data reuse are provided for authors, reviewers, editors and readers.

"One of the main obstacles to genuine intellectual productivity in contemporary academia is that most scholars publish too much" [Stefan Collini in his foreword to *The Slow Professor* (Berg and Seeber, 2016)].

1. Using the same data more than once

Our careers as scholars in Operations and Supply Chain Management (OSCM; which is assumed here to subsume Purchasing and Supply Management, PSM) are to a large extent dependent on our productivity in publishing (Grant et al., 2018). At many schools, tenure decisions hinge on how many papers have been published and in which journals. Following the old adage of "what gets measured, gets done", scholars seeking tenure and other forms of career advancement are firmly focused on publishing. Despite efforts to develop more balanced dashboards for faculty performance, the number of publications (possibly corrected for the number of co-authors, the quality of the journals and/or the 'impact' of the publications) is still the single most important performance indicator in science (Tachibana, 2017).

This strong focus on publication productivity stimulates scholars to seek efficiency in scholarly research (Drotar, 2010; Honig and Bedi, 2012). For those researchers with the ambition to publish empirical work, data collection is often a time-consuming activity where efficiency gains could perhaps be found. Some scholars seek efficiency in joining multi-country research consortia, whereby data collection in the home country is rewarded with access to the dataset from all participating countries. Others seek efficiency by investing in one big data collection effort (e.g., for their PhD dissertation) and planning for multiple papers from one data collection effort. With careful upfront planning, and transparency, consistency and integrity in its execution, this approach supports the need for valuable empirical contributions to the OSCM field (Flynn et al., 1990; Filippini, 1997; Fisher, 2007). Theoretical advancement of our field is not served however when a dataset is 'harvested' through piecemeal publication (Drotar, 2010) across multiple articles.

While there are good reasons for publishing multiple articles out of one dataset, and also good examples of how this is done in our field, this Notes and Debates article is about the limits to data reuse. Data reuse across multiple publications is not considered a problem a priori. Data collection can mean huge effort, and putting a painstakingly created dataset to multiple use may seem a valid choice from a standpoint of research efficiency. But, when does the drive toward efficiency go too far? When does the reuse of data cross the line from efficiency into the territory of questionable research practices, or worse?

Using the same dataset in multiple publications might mean crossing into self-plagiarism, duplicate publication, redundant publication, overlapping publication and salami publication (a.k.a. 'slicing and dicing') (Martin, 2013). The U.S. Office of Research Integrity describes self-plagiarism as a collection of practices "in which some or all elements of a previous publication (e.g., text, data, and images) are reused in a new publication with ambiguous acknowledgement or no acknowledgement at all as to their prior dissemination […] laying in a

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continuum in which the extent and the type of duplication can vary from substantial to minor, as does their potentially serious effects on the integrity of the scientific record" (ORI, 2017).

A survey in 2007 among all editors of Wiley-Blackwell journals identified redundant publication as the most severe and most frequently occurring form out of 16 forms of research misconduct, the next five in terms of severity and frequency being plagiarism, duplicate submission, undisclosed authors conflict of interest, undisclosed reviewer conflicts of interest, and gift authorship. However, all forms were reported to occur rarely. This survey also indicated low levels of awareness of research misconduct among editors (Wager et al., 2009).

A variety of examples of multiple uses of the same dataset exist in our field of Operations and Supply Chain Management. First, there are the widely known research consortia, such as the Global Manufacturing Research Group (GMRG), the International Manufacturing Strategy Survey (IMSS), the High Performance Manufacturing (HPM) consortium, and the International Purchasing Survey (IPS). The datasets generated by these consortia are used in many publications. Using the first two consortia names as keywords in Google Scholar resulted in over a thousand hits. (The other two consortium names have a higher risk of false positives in the results.) All of these publications explicitly mention the consortium as the source of the data, acknowledging that the authors are using data that is also available to other researchers, and readers can thus identify other publications based on the same data.

There are also examples of data collected by an individual or a research team, where later publications acknowledged the earlier use(s) of the data. In these cases, the authors typically explained to the reader how the later publication is different from the earlier publication(s), and what the additional contributions of the later publication(s) are. In our work as (associate) editors, we have also seen such best practice examples, in which authors took care to be transparent about the reuse of data in multiple papers.

But, there are cases in which the reuse of the same dataset was not explicitly mentioned, but only became apparent by carefully reading the research method sections of the concerned publications. In cases like this, it is not made clear to the reader that multiple publications used overlapping data from the same dataset, nor are later articles discussed in light of earlier contributions. As the boundaries between legitimate reuse of data and deceitful salami slicing are hazy (Beaufils and Karlsson, 2013), the aim of this Notes and Debates article is to explicitly identify problematic practices associated with this type of opaque data reuse. With this effort, we want to contribute to a debate of where the boundaries lie between well-executed reuse of overlapping data in multiple publications, and indefensible harvesting of datasets.

2. Standards

In many areas of research, conditions are specified under which circumstances two or more publications could legitimately rely on the same dataset (cf. Fine and Kurdek, 1994). In our field, Associations and Journals provide the following guidelines. Elsevier, the publisher of the Journal of Operations Management and the Journal of Purchasing and Supply Management, considers "salami slicing", defined as "breaking up or segmenting data from a single study and creating different manuscripts for publication", an unethical and unacceptable practice (Elsevier, 2015). The Journal of Supply Chain Management instructs authors to "inform the Editors if any part of the data in the submission have been published elsewhere. Such publication does not automatically disqualify a paper from submission to JSCM. However, the authors must make this disclosure". And "JSCM submissions must explicitly cite works of others or their own. Works include text, ideas, creative works, and data, etc." (JSCM, 2017). The Academy of Management Code of Ethics (version of February 2006) contains two Ethical Standards that are relevant to this topic:

> "4.2.1.2. AOM members explicitly cite others' work and ideas, including their own, even if the work or ideas are not quoted verbatim or paraphrased. This standard applies whether the previous work is published, unpublished, or electronically available."

> "4.2.3.5. When AOM members publish data or findings that overlap with work they have previously published elsewhere, they cite these publications. AOM members must also send the prior publication or in-press work to the AOM journal editor to whom they are submitting their work" (AOM, 2006).

The Production and Operations Management Society (POMS) has also included the above standards of scholarly behaviour in their Ethical Guidelines for Authors and Reviewers (POMS, 2017).

Standards for using data in multiple publications vary from 'unacceptable' to 'inform the Editors' and 'inform the readers via citations to the other work(s)'. In the field of OSCM, data is being reused across multiple publications, and there is clear evidence that the Editor is not always informed, nor is the reader always informed via citations to the other publications. If we accept that there should be room to allow for multiple publications from one dataset, the question arises under what circumstances this reuse may become problematic. This Notes and Debates article was triggered by two cases of extensive, yet undisclosed data reuse within the field of OSCM.

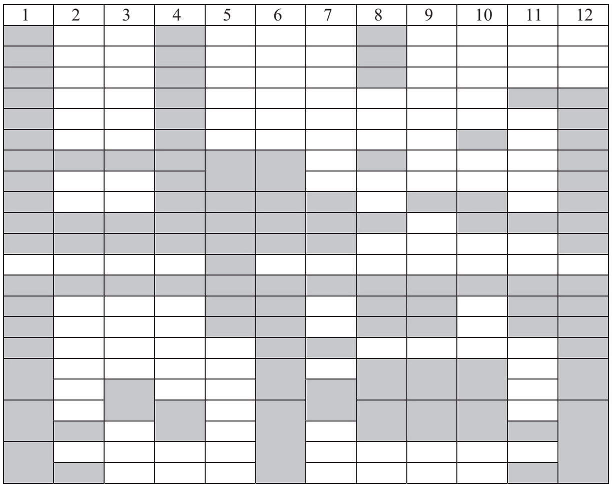
3. Two cases from the OSCM field[1]

Two cases of extensive data reuse were analysed to get an in-depth understanding of what types of problems may occur when the same data is used across multiple articles. These are cases in which the same dataset was used across all articles within one case, i.e. one dataset stemming from one data collection effort, and in which there is substantial overlap in the parts of the dataset – the "data slices" – that are used across articles. The two cases being analysed each include twelve articles. Fig. 1 provides a visual depiction of the extent of data overlap across the two cases. Panel A represents the first case, panel B the second. Each column represents a publication. Each row represents a single item or multi-item construct. A shaded cell indicates inclusion of that construct in the data analysed in that article. It is this use of overlapping data slices that creates most of the problems and is the focus of this Notes and Debates article.

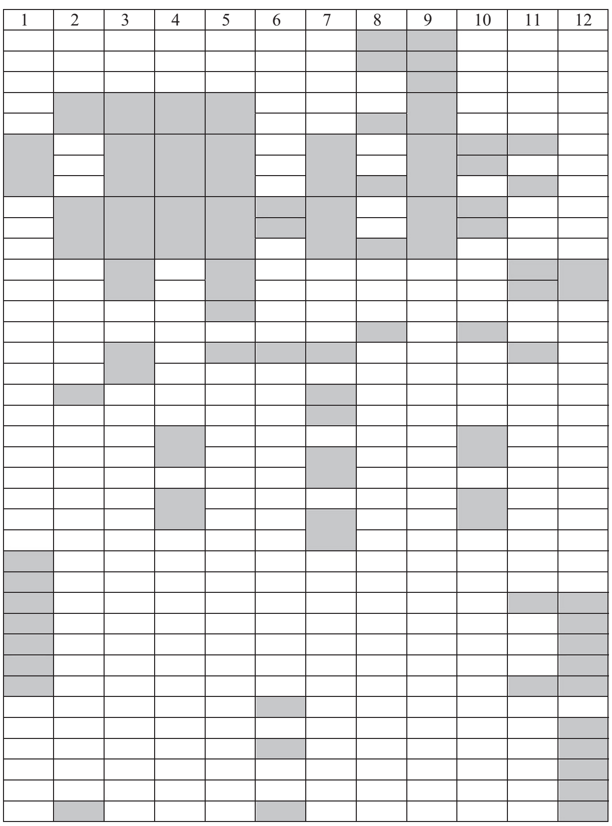
Both cases were identified more or less coincidentally. When reading a publication that looked familiar (hence the title "déjà lu") similarities were noted in the methods sections of the new publication and the earlier one. Google Scholar then helped to identify the other publications with almost identical methods sections. Following a heuristic suggested in Wood (2008), articles were checked for shared authorship, similar study design, and similar sample characteristics.

Both cases concern survey research. In both cases, twelve journal articles were identified presenting multi-variate analyses using the same dataset. In each case, one individual is an author on all journal articles, though not always the first author. Conference papers and publications in (lower reputation) journals without full-text access were excluded from analysis. Taken together, these 24 articles were published between 2004 and 2017. Across the two cases, the articles have been published in the core journals of our field, including Journal of Operations Management, Production and Operations Management, Journal of Supply Chain Management, Journal of Purchasing and Supply Management, International Journal of Production Research, International Journal of Production Economics, Journal of Business Logistics, Supply Chain Management: An International Journal, International Journal of Physical

[1] The purpose of this Notes and Debates article is purely educational. In order to not reveal the identity of the authors, only general descriptives are provided here. The Editors-in-Chief of the Journal of Purchasing and Supply Management have seen the evidence underlying these analyses.



Panel A: Data overlap across the twelve articles in case 1.



Panel B: Data overlap across the twelve articles in case 2.

Fig. 1. Data overlap across the 24 articles in the two cases. Each column represents an article and each row represents a single item or multi-item construct. A shaded cell indicates inclusion of that construct in the data analysed in that article. A cell merged across multiple rows indicates that in that article, a construct was used that combined items used for separate constructs in another article.

	#
1A	12
1B	11
1C	4
1D	1

Panel A: Authorship across the twelve articles in case 1.

	#
2A	12
2B	9
2C	3
2D	3
2E	2
2F	2
2G	2
2H	1
2I	1
2J	1
2K	1
2L	1
2M	1
2N	1
2O	1

Panel B: Authorship across the twelve articles in case 2.

Fig. 2. Authorship across the 24 articles in the two cases. Each row represents a different author. The numbers in the second column show on how many of the twelve articles this individual was an author.

Distribution and Logistics Management, and some in journals that are not core to the OSCM field. Most of the publications use structural equation modelling as the main data analysis method, followed by cluster analysis, and regression analysis.

Fig. 2 illustrates how authorship is distributed across articles in the two cases. The numbers in the second column show how often the person in each row was an author on the twelve articles of each case. The figure shows that the set of authors collaborating across the twelve articles in case 1 was much more condensed (four authors in total) than in case 2 (15 authors in total).

The publications that are part of these two cases have a real impact on our field. Some of these publications are in our top journals and have more than a thousand citations in Google Scholar. The publications are used in meta-analyses. While, fortunately, most meta-analytic studies have included only one article from a set, the first meta-analysis including two publications of one set (and hence inadvertently using the same data twice) has recently been published. Considering that together, these two publications represented more than 50% of the size of the meta-analytical sample, the distortion provided by this double inclusion is non-trivial.

Articles citing multiple publications based on one dataset are seen, and presented as if these are references to different research studies. First, as self-citations, with authors from the above cases citing multiple of their own publications from the same dataset as if they represent different studies. Second, authors not connected to these cases cite multiple publications from the same dataset as if they represent separate studies. The latter likely concerns unsuspecting colleagues from our OSCM field. These are only examples of some of the problems inherent in cases involving multiple uses of data. However, there are others that need further discussion.

These two cases are not the only ones in the field of OSCM. After the analyses underlying this Notes and Debates article were completed, a third case was identified with 14 publications based on the same set of survey data, published in our top journals. There were ten different authors on these publications, with two of those on each publication. Moreover, we have data on a case with 24 publications based on four survey datasets that are combined in various ways across those 24 publications, and a case with 18 publications based on varying combinations of five primary datasets. Again, the repeated use of the same dataset spans across more than a decade in all three additional cases. Beyond these, there are several other examples of 4–8 publications using the same dataset. In all these cases, the reuse of overlapping data is not made transparent to the reader.

As previously stated, using one dataset across multiple publications is not a problem per se. But, the more publications there are stemming from one dataset, the greater the risk of running into problems with self-plagiarism, lack of marginal contribution, and inconsistencies across publications. The two cases being analysed here, with twelve publications each, are in a sense 'extreme cases', but they are certainly not the only two, and they are probably not even the most extreme.

4. Eighteen problematic practices

Eighteen problematic practices were identified that can occur from the second publication onward when a dataset is used for more than one publication. General insights of best practices in empirical research were built on to help define these practices. These include:

- formulating hypotheses before the data are collected;
- defining measurement instruments and multi-item constructs before data are collected;
- collecting data specifically to test the hypotheses for a certain study;
- defining rules for excluding data points before data are collected;
- providing transparency about the complete data collection instrument;
- providing transparency about how and why data points were excluded (if any);
- including all variables that might confound the relationship(s) of interest;
- providing transparency with respect to all relevant details of the research methods employed.

The eighteen problematic practices are defined in Table 1, subjectively ranked by degree of severity. The most severe problems (10 − 18) clearly cross the line into the area of research misconduct. Where we refer to the "reader", this could be a reader who is reading a published paper, or an editor or reviewer who is assessing a manuscript submitted for publication. The list resulted from asking the question: What makes us feel uneasy reading the 10th, 11th and 12th publication, knowing that there are nine earlier publications based on exactly the same dataset? As readers, we would like to know of these earlier publications. Do the authors provide transparency about prior data use? If there are all these earlier publications, the data is probably quite old. Do the authors mention the age of the data? If there are these earlier publications, then the data was not collected specifically for the purpose of testing the hypotheses of the later publications. Are the authors clear about this, or do they suggest otherwise? If there are so many earlier publications based on the same dataset, what then exactly is the contribution of this later publication? How does the later publication relate to the earlier publications? Do later publications take into account what the authors already know from their analyses presented in earlier publications? The eighteen problematic practices were identified when analysing the 24 publications with these kinds of questions in mind. A full analysis of one case against all eighteen practices is very time-consuming, but a quick scan of the additional cases mentioned above did not lead to the identification of problematic practices that are not already listed in Table 1.

The first two practices, of the rather "innocent" type, concern not revealing the fact that the same data was used in earlier publications, and not revealing the age of the data. Practices 3 and 4 are somewhat related and are about not revealing to the reader that the data collection and the measurement instrument were actually not specifically designed for the study that is reported in the publication at hand, but were designed/developed for an earlier study (e.g., an underlying dissertation). The gold standard of research would assume that the measurement instruments are based on the state-of-the-art knowledge at the time of design. Practices 5 and 6 show violation of this gold standard, as they illustrate the authors' flexibility in what references to use as support for measurement instrument design, through the use of inconsistent references for measurement instruments and/or the use of references that are more recent than the data collection effort (e.g., more recent than the first publication using the same data). Practices 7–9 illustrate different ways of using questionnaire items inconsistently across publications. Practice 9 could defensibly occur as a result of measurement purification, but without transparency to the reader, this type of measurement inconsistency should be seen as problematic.

Practices 10 and 11 both concern contradictions between publications. Practice 10 concerns the reporting of different numbers of data points across publications without proper explanation of why certain data points were excluded in one publication and not in the other. Practice 11 is about making other types of contradictory statements (related to data collection or data analysis) across publications without due explanation. Practices 12 and 13 are both related to the use of earlier publications from the same dataset as if they provide independent support for study design in a later publication. Either as independent support for hypothesis development (practice 12) or as independent support for methods development (practice 13). This represents an unacceptable form of circular reasoning.

Practice 14 is an example of conveniently ignoring earlier publications from the same dataset. The gold standard for research would state that known confounders should be included in data analysis, and practice 14 violates this standard. Practices 15 and 16 are about the use of earlier publications in the interpretation of the data as if these earlier publications represent independent studies. Earlier publications can be used misleadingly as corroborating proof for findings in a later publication (practice 15), or a misleading claim can be made that a later publication makes an empirical contribution vis-à-vis earlier publications (practice 16). Practice 17 is again about conveniently ignoring earlier work, but in this case to claim that certain data are not available in the dataset, while earlier publications have already shown that they are. Note that this practice can only be identified because there is an earlier publication with proof that the data exist. This practice could be occurring much more frequently, without evidence for its existence, when there are no earlier publications to expose this practice. Practice 18, finally, concerns duplicate publication, when essentially the same hypotheses are tested in more than one publication in the set. Note that we have not included self-plagiarism of texts in our list, but the risk of this practice is high, in particular across the sections of text describing study design and research methods.

There is evidence of all eighteen problematic practices in the sets of published articles analysed in preparing this article. We do not know of course what level of transparency was provided to the respective OSCM journal editors upon submission of the manuscripts; the analysis is necessarily just focused on the final publications. Note that these problems can occur when exactly the same dataset is used across multiple publications and when the datasets across different publications are largely the same as a result of data augmentation, aggregation or disaggregation (see ORI, 2017b). Some of these problems (e.g., the "milder" problems 2–4) can also occur in papers that use a dataset only once. It is important to note that changing norms regarding publishing requirements over the last twenty years (mostly norms becoming more stringent) may have changed the severity of some (but not all) of these problems. Requirements for disclosure are now more advanced. Within each discipline, definitions of what is acceptable and unacceptable must be continuously updated.

The frequencies with which these problematic practices occurred in the 24 publications of the two cases are presented in Fig. 3. Every one of the eighteen problematic practices has been observed in the two cases combined, with fourteen of them (including the seven most problematic) occurring in both cases. The 'less problematic' practices (1–4) occur very frequently: the fact that the same dataset was used in earlier publications was usually not mentioned, nor was the year of data collection. It was generally implied that the data were collected specifically for this publication, and that the data collection instrument was developed for this one study.

A significant difference between the two cases is that in case 2, earlier publications using the same dataset are far more frequently used as sources to support hypothesis development, or to suggest that they provide corroborating evidence for findings in the discussion sections

Table 1
Eighteen problematic practices related to data reuse across multiple publications, and their implications.

	Label	Problematic practice	Impact
P1	Concealing prior data use	Not being transparent about the existence of earlier publications that used the same dataset for analysis.	This lack of transparency hinders readers in their assessment of the extent to which the findings presented are new relative to what has already been published.
P2	Concealing data age	Not being transparent about the age of the data.	This hinders readers in assessing to what extent they believe the findings to (still) be valid at the time of publication.
P3	Implying dedicated data collection	Suggesting that the data were collected specifically for this one article.	This suggests that a best practice in empirical research was followed, while the sample and/or the data might actually not be the best fit with the variables that are studied and the hypotheses that are being tested.
P4	Implying dedicated measurement	Suggesting that measurement instruments were developed specifically for this one study.	This suggests that a best practice in empirical research was followed, while the measurement instruments might actually not be the best fit with the variables that are studied and the hypotheses that are being tested.
P5	Referencing inconsistently	Using different references for measuring similar constructs across papers.	This shows that the measurement model was not defined ex ante but suggests that it was created after the data were collected (and analysed).
P6	Implying recency of data collection	Using references for measurement instruments that are more recent than the data collection effort.	This suggests that the measurement model was created after the data was collected (and analysed) and that the authors are capitalizing on the chance of finding significant relationships between variables. This practice could also be used to pretend the study links to more recent work than it actually does.
P7	Re-using items inconsistently	Using the same indicators (items) and indicator sets for different constructs across papers.	This hinders readers in assessing whether a construct that looks like it is new in the nomological net is actually overlapping with existing constructs. It hinders meta-analytical studies and it suggests theoretical contributions that are actually not there.
P8	Labelling constructs inconsistently	Using different labels across papers for constructs that have the same indicator set.	This hinders readers in assessing whether a construct that looks like it is new in the nomological net is actually overlapping with existing constructs. It hinders meta-analytical studies and it suggests theoretical contributions that are actually not there.
P9	Building constructs inconsistently	Using different indicator sets for a construct with the same label across papers.	In contrast to the problem above, this means that a construct that looks like it is the same in the nomological net is actually a different construct. Again, this hinders the accumulation of knowledge and meta-analytical studies.
P10	Concealing inconsistent data point exclusion	Using different rules for including or excluding observations across papers without due explanation.	This suggests that decisions about including or excluding data points were made after the data were collected (and analysed) and that the authors are "massaging the data" in order to find significant relationships between variables.
P11	Self-contradicting, without explanation	In later papers using the same data, making statements which contradict earlier publications, without reference to those earlier publications.	This suggests that the successful publication of the individual paper is more important than the process of cumulative knowledge development across studies.
P12	Recursive hypothesis building	Citing an earlier publication based on the same dataset as empirical support for hypotheses developed in later papers.	With this practice, the reader is fooled into believing that there is reason to propose a certain hypothesis, while the author(s) already knows that the same dataset will be in support of that hypothesis.
P13	Recursive methods development	Citing an earlier publication based on the same dataset as if it was an independent source from which research methods were adopted or adapted.	The reader is fooled into believing that those earlier publications provide independent support for the quality of the research methods.
P14	Ignoring known confounders	Not including variables in analyses in a later paper that were shown in an earlier publication to correlate with variables that are also used in the later paper.	The reader is fooled to believe that there is no knowledge of variables that confound the relationship(s) as presented.
P15	Falsely claiming corroboration	Suggesting that earlier publications (using the same data) provide independent corroborating proof for findings in later papers.	This practice implies the accumulation of knowledge across studies is suggested, but this is no more than a trick to increase the credibility of the later paper.
P16	Falsely claiming empirical contribution	Suggesting that a later paper provides an empirical contribution (e.g., a replication) to earlier publications that used the same dataset.	A later study can only make an empirical contribution to a debate (for example through a replication study) if it studies the same phenomenon or relationship using new data. This practice claims accumulation of knowledge which is not there.
P17	Denying the existence of inconvenient data	Discussing unmeasured items or constructs as a limitation in one paper, while from other publications using the same dataset, it is clear that those items or constructs were measured and available.	This can only be classified as a lie to the readers.
P18	Concealing duplication	Testing essentially the same hypotheses again in a later paper without reference to the earlier publication(s).	This is a clear case of duplicate publication / self-plagiarism.

	1	2	3	4	5	6	7	8	9	10	11	12
P1		X	X	X	X	X	X	X	X	X	X	X
P2	X	X	X			X	X	X	X	X	X	X
P3	X	X	X	X	X	X	X	X	X	X	X	
P4	X	X	X	X	X	X	X	X	X	X	X	
P5			X	X	X							
P6												
P7		X				X		X		X	X	
P8			X	X								
P9							X	X		X	X	X
P10									X			
P11												
P12											X	
P13		X			X						X	X
P14										X	X	
P15						X				X	X	X
P16											X	
P17			X				X					
P18			X									

Panel A: Occurrence of problematic practices across the twelve articles in case 1.

	1	2	3	4	5	6	7	8	9	10	11	12
P1		X	X	X	X	X	X	X	X		X	X
P2	X	X	X	X	X	X	X	X	X	X	X	X
P3	X	X	X	X	X	X	X	X	X		X	X
P4	X	X	X	X	X	X	X	X	X		X	X
P5			X		X		X	X				
P6			X		X			X	X			X
P7					X	X				X	X	X
P8							X					
P9			X		X	X	X	X		X		X
P10												
P11		X				X					X	
P12				X	X	X	X	X	X	X	X	
P13				X					X			X
P14					X		X			X		
P15				X	X	X	X		X	X	X	X
P16				X			X		X			
P17		X										
P18											X	

Panel B: Occurrence of problematic practices across the twelve articles in case 2.

Fig. 3. Occurrence of the eighteen problematic practices across the 24 articles in the two cases. Each column is an article, and each row represents the respective practice from Table 1.

(practices 15 and 16). Most of the 'more problematic' practices (10 − 18), occur in both cases, although contradictions between publications (practice 11) were not found in case 1, and differences in number of data points used (practice 10) were not found in case 2. All in all, the rate of occurrence of the problematic practices is disturbing.

One striking feature across the two cases is the "creativity" with which multi-item constructs are created. Problems 7–9 represent three different practices in this regard: using the same indicators (items) and indicator sets for different constructs across publications; using different labels across publications for constructs that have the same indicator set; and using different indicator sets for a construct with the same label across publications. We present examples of this in Fig. 4.

In panels A and B of Fig. 4, each row stands for an item (one question in the questionnaire). Each column stands for a publication. The letters in the cells stand for a construct. If a construct name is different between publications, a different letter is used, even if the items may be the same. If a construct name is the same, but the underlying items are not, an apostrophe is used to signify this. These panels show only a part of the complete items-*per*-publication analysis that was conducted. In case 1 there are only four out of 39 items that are used consistently for one and the same construct: i12, i13, i38 and i39. All other 35 items are used in multi-item constructs with different labels across publications and/or in different combinations to create constructs across publications. In case 2, there are three consistently used items out of 33: i1 to i3. The inconsistencies in combining items and labelling multi-item constructs are clear from Fig. 4, but due to the lack of cross-references between articles in each case, these inconsistencies are hidden from the readers' view.

5. Causes and consequences

Many of the above problematic practices can be related to

	1	2	3	4	5	6	7	8	9	10	11	12
i1	A	A	A	B	A’	A’’		B’				A
i2	A	A	A	B	A’	A’’		B’				A
i3	A	A	A	B	A’	A’’		B’				A
i4	A	A	A	B	A’	A’’		B’				A
i5	A	A	A	B	A’	A’’		B’				A
i6				B	A’	A’’						
i7				B	A’	A’’						
i8	C			C	A’	A’’						C
i9	C			C	A’	A’’						C
i10	C			C	A’	A’’						C
i11	C			C	A’							C
i12	C			C								C
i13	C			C								C
i14	D	E	D	B	D’	D	F	B’		D	G	D
i15	D	E	D	B	D’	D	F	B’		D	G	D
i16	D	E	D	B	D’	D	F	B’		D	G	D
i17	D	E	D	B	D’	D	F	B’		D	G	D
i18				B	D’							
i19				B	D’							
i20	H	J	H	B	H	J	F					J
i21	H	J	H	B	H	J	F					J
i22	K	K	K	B	K’	L	F	B’	M	N	G	N’
i23	K	K	K	B	K’	L	F	B’	M	N	G	N’
i24	K	K	K	B	K’	L	F	B’	M	N	G	N’
i25	K	K	K	B	K’	L	F	B’	M	N	G	N’
i26	K	K	K	B	K’	L	F	B’	M	N	G	N’
i27				B	K’					N		
i28	O				P	Q		B’	M		G	O
i29	O				P	Q		B’	M		G	O
i30	O				P	Q		B’	M		G	O
i31	O				P	Q		B’	M		G	O
i32	O				P	Q		B’	M		G	O
i33					P	Q						
i34	R				S	T		B’	M		G	S’
i35	R				S	T		B’	M		G	S’
i36	R				S	T		B’	M		G	S’
i37	R				S	T		B’	M		G	S’
i38					S							
i39					S							

Panel A: Item reuse across the twelve articles in case 1.

	1	2	3	4	5	6	7	8	9	10	11	12
i1			A	A	A				A			
i2			A	A	A				A			
i3			A	A	A				A			
i4		A’	A	A	A			B	A			
i5		A’	A	A	A			B	A			
i6		A’	A	A	A			B	A			
i7		A’	A	A	A			B	A			
i8		A’	A	A	A				A			
i9		A’	A	A	A				A			
i10	C		C	C	C		C		C	D	E	
i11	C		C	C	C		C		C	D	E	
i12	C		C	C	C		C		C		E	
i13	C		C	C	C		C		C	F		
i14	C		C	C	C		C		C	F		
i15	C		C	C	C		C		C	F		
i16	C		C	C	C		C	G	C			
i17	C		C	C	C		C	G	C		H	
i18	C		C	C	C		C	G	C		H	
i19	C		C	C	C		C	G	C		H	
i20	C		C	C	C		C		C		H	
i21			J	J	J	K			J	L		
i22			J	J	J	K			J	L		
i23			J	J	J	K	J’		J	L		
i24		J’’	J	J	J	M	J’		J	N		
i25		J’’	J	J	J	M	J’		J	N		
i26			J	J	J	M	J’		J	N		
i27			J	J	J		J’		J			
i28		J’’	J	J	J		J’	O	J			
i29		J’’	J	J	J		J’	O	J			
i30		J’’	J	J	J		J’	O	J			
i31		J’’	J	J	J		J’	O	J			
i32		J’’	J	J	J		J’	O	J			
i33		J’’	J	J	J		J’	O	J			

Panel B: Item reuse across the twelve articles in case 2.

Fig. 4. Illustrations of item reuse across the 24 articles in the two cases. Each row is an item (one question in the questionnaire) and each column is an article. Items with the same letter in one article were used together in a multi-item construct. Constructs A, A' and A" have the same label in different articles, but consist of different item sets (similarly for B and B', etc.). Constructs D and E have exactly the same items, but different names across articles (similarly for H and J, etc.). Constructs B, B', F, G and M are second-order constructs. Panel A and panel B only show a subset of the total number of items used across all articles.

'HARKing' – Hypothesising After the Results are Known (Kerr, 1998; Bosco et al., 2016) – and p-hacking – running multiple statistical tests, but reporting only those that delivered 'publishable' results (Schwab and Starbuck, 2017). In fact, they are not just about hypothesising after the results are known, but also creating multi-item constructs after the results are known, and deciding about data point exclusion after the results are known. HARKing and p-hacking capitalize on the chance that in any given dataset, there will be significant relationships between items and/or between variables. The chances increase when one chooses to be flexible in how to combine indicators into constructs and/or flexible in which data points to exclude from analysis. The pressure to publish and the bias of journals towards publishing positive results are seen as reasons why authors engage in HARKing and p-hacking (Bosco et al., 2016; Hollenbeck and Wright, 2017; Schwab and Starbuck, 2017).[2]

Some of the eighteen problematic practices may also stem from a willingness to adjust manuscripts in order to increase chances of the paper being accepted (Martin, 2013). The theme of a special issue may lead authors to relabel their variables. The aims and readership of the target journal may lead authors to refer to a different set of publications as support for their measurement model, using sources from that journal or articles authored by that journal's editor(s). Asserting that best practices were followed while in fact they were not, is another example of researchers choosing to be flexible.

The eighteen practices undermine the quality of the scientific record and hinder the progress of scientific knowledge development in the field of OSCM. These practices serve only to increase the authors' number of publications and are part of a game in which we fool each other, to a greater or lesser extent, with 'scientific findings'. Covert duplicate publication of results wastes the time and resources of the editors, the reviewers and the readers; it can distort findings in meta-analyses; and it undermines the integrity of science (Von Elm, 2004). Dishonesty destroys the academic project from within by violating the founding principles of science and academic work (Hansson, 2000).

It is worth considering whether this behaviour is intentionally opportunistic ('self-interest seeking with guile'), a 'white lie' without intention to harm, or a case of 'honest incompetence' or carelessness (Hansson, 2000; Hendry, 2002; Hodgson, 2004; Martin, 2013). Readers might assume that authors in the two sets of articles presented here are either unaware of the norms required in high quality journals, or are inexperienced researchers. However, in both cases some of the authors are/were affiliated with reputable universities in Western Europe/North America. Furthermore, the authors on the articles – 19 different authors altogether on the 24 articles – constitute a mix of early career academics and very experienced scholars. Therefore, the practices cannot only be attributed to differences in national research standards, to inexperience, or to the pressure to achieve tenure (cf. Honig and Bedi, 2012; Martin, 2013).

Discussions with (young) scholars in the OSCM field bring out the fact that there is an education/training problem and that supervisors and research methods instructors have not necessarily discussed HARKing in both its secret and its transparent form (Hollenbeck and Wright, 2017). The list of eighteen problematic practices set out in this article should be a useful resource for research training, aiding discussion about acceptable and unacceptable research practices. At the very least, discussion surrounding what is appropriate and inappropriate should introduce some objectivity into the process.

Academics engaging in these eighteen practices set a poor example to the next generation of OSCM scholars (cf. Honig et al., 2014). As long as these 'highly efficient' research practices are associated with productivity, success, and career progress, the temptation to practice this kind of 'fast science' remains high. The field of OSCM should become more sensitized to these practices and prevent this from becoming the norm, through more vigilant reviewing and editing, and through research training. Given evidence of unsuspecting authors citing two articles based on the same dataset as if they were citing two independent studies, all of us should also treat past research with more caution.

6. Recommendations

The evidence and discussion presented above show that there are many potential problems when the same data are used across multiple articles. Adherence to a set of guidelines might help avoid these problems. Drawing on others' advice, and focusing on survey-based research especially, this article concludes with some recommendations. For authors, these relate to transparency and consistency. For readers, reviewers and editors, vigilance is needed.

Before data collection, hypotheses should be formulated, measurement instruments developed on the basis of state-of-the-art literature should be captured in a codebook, and rules for excluding observations should be formulated. If data are collected as part of an (international) research consortium, the research protocols and the codebook should be agreed upon by all consortium partners and followed by all users of the database. Consortium members should keep each other informed about empirical analyses run on the data, such that they are all aware of potential co-variates in research models. Rules for including and excluding observations should be agreed by all consortium members. Clearly, there are many more challenges to publishing consortium-based international survey research than Harzing et al. (2013)'s recommendation to avoid "too much overlap in variables and theoretical perspectives" between publications.

As an illustration of such challenges, a quick review of publications from well-known consortia in OSCM shows that different publications by the same authors report different numbers of observations even though the data come from the same round of data collection. Kirkman and Chen (2011) recommend that if a dataset is collected with the intent to publish multiple papers from that dataset, the separate papers are crafted and designed from the inception of the project. A so-called 'uniqueness analysis' (p. 435) can underpin such a multiple paper publishing strategy. In essence, this is a table showing how the various papers differ or overlap regarding research question, theories used, constructs/variables used, theoretical and managerial implications.

In all publications from the same dataset, readers must be able to assess how much the additional paper contributes to existing knowledge. Transparency is key. Authors must provide transparency to the Editors as well as to the readers. Drotar (2010) and Kirkman and Chen (2011) provide helpful advice on what to include in the cover letter to the Editor(s), but also on how to explain each paper's uniqueness to the reader. As they state, it is always best to err on the side of transparency, and the onus is on authors to convince the Editor that there is merit in submitting multiple manuscripts from the same study. As an example, the Journal of Organizational Behavior has included the following in their author guidelines: "If the dataset in the manuscript has been used in a previously published study or if the dataset is currently under review elsewhere, the authors will need to provide a data transparency table as part of the submission process (this will not be part of the actual submitted manuscript). This table should list all of the variables from the dataset and all of the studies coming from the data, and demonstrate the independence of each of the manuscripts developed from the shared dataset" (JOB, 2018). The American Psychological Association provides examples of a Data Transparency Appendix, which could take a narrative and/or table format (APA, 2018).

Whether or not reviewers should also know about data overlap depends on a journal's policy towards double-blind reviewing, since

[2] Hollenbeck and Wright (2017) distinguish between Sharking (Secretly HARKing in the Introduction section) and Tharking (Transparently HARKing in the Discussion section). In this new nomenclature, we are referring here to the unethical practice of Sharking.

telling reviewers about data overlap would normally mean revealing the authors' identities. Some journal Editors believe author anonymity should be preserved (e.g., Colquitt, 2013), while others find transparency towards reviewers more important than author anonymity (e.g., Kirkman and Chen, 2011). Whatever the journal's policy, editors must receive all relevant information from the authors; full disclosure on data reuse in correspondence accompanying the submitted paper is essential.

In addition to transparency, consistency is also critical (Drotar, 2010). It is important to use a consistent measurement model from one publication to the next. Consistency in rules for how to count the number of responses should ensure that the gross number of observations is the same across papers. Missing values for particular items may lead to differences in data points used for analysis, but this should be made transparent to the reader. Consistency across papers also means that co-variates identified in an earlier publication are included in the analyses in later papers. Later papers must not be written as if the earlier paper(s) do not exist.

Readers need to be more vigilant when reading and interpreting published research. This caution of vigilance is particularly important for researchers executing meta-analytic research (Von Elm et al., 2004; Wood, 2008).

Editors and reviewers have an important role in protecting the integrity of the publication record. Inconsistencies across publications, and even the practice of HARKing, may result from suggestions that reviewers make in the review process. Authors should be trained to resist suggestions that they feel compromise the integrity of their work, and reviewers should be trained not to ask for changes that may result in inconsistencies or even breaches of research integrity. We must acknowledge that there are issues of power and dependence between authors and reviewers, and the handling editor is probably in the best position to deal with such issues. Hence, associate editors also need proper guidance from editors-in-chief for handling these situations.

Our analyses have shown that the OSCM publication record contains many publications with one or more of the eighteen problems. Should the record be cleaned up ex post? Perhaps more important is to try to identify these problems in manuscripts that are submitted to our journals. It may require even clearer author guidelines, and tick boxes in manuscript submission systems asking authors to declare whether or not the data overlaps with data used in earlier publications (cf. Colquitt, 2013).

7. Conclusion

Data reuse is not a problem per se, but an analysis of actual cases of using the same data across multiple publications shows that data reuse may be associated with questionable research practices. The problem of excessive and inappropriate data reuse is not unique to the field of Operations and Supply Chain Management. Martin (2013) describes various detailed cases of self-plagiarism from his experience as Editor of Research Policy, and the reference list provides evidence of the existence of similar problems in psychology, general management, and medical research. Avoiding these problems is a necessary, but not a sufficient condition for data reuse to be acceptable. The most important question is whether each separate paper makes a sufficiently significant contribution to the literature, or whether it would be better to integrate the work and publish fewer articles each making a more substantial contribution.

Are these cases examples of a practice we could call 'fast science' – a science that is entirely focused on efficiency and productivity (as in 'fast food' or 'fast fashion')? Let us hope that in science, akin to the 'slow food' and 'fair fashion' counter-movements, the pressure to publish often is replaced by the pressure to publish wisely (Parke, 1994). Authors, reviewers, editors and critical readers can all contribute to a system in which fast science of the kind described here is recognised and no longer rewarded. It is our hope that the explicit identification of these eighteen problematic practices in the re-use of data contributes to such a development.

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