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Discussion paper (201106)



Explanation of symbols

.	= data not available
*	= provisional figure
**	= revised provisional figure
x	= publication prohibited (confidential figure)
–	= nil or less than half of unit concerned
–	= (between two figures) inclusive
0 (0,0)	= less than half of unit concerned
blank	= not applicable
2010–2011	= 2010 to 2011 inclusive
2010/2011	= average of 2010 up to and including 2011
2010/'11	= crop year, financial year, school year etc. beginning in 2010 and ending in 2011
2008/'09–2010/'11	= crop year, financial year, etc. 2008/'09 to 2010/'11 inclusive

Due to rounding, some totals may not correspond with the sum of the separate figures.

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Representativity of VAT and survey data for short term business statistics

Pim Ouwehand and Barry Schouten

Summary: Monthly Short Term Business statistics at Statistics Netherlands can be based on survey data, VAT records or a combination of these two data sources. Both sources are incomplete when statistics need to be produced. The survey response rate increases gradually in time and is still far from 100% after a month of data collection. The VAT register also fills gradually in time because i) quite some enterprises report on a quarterly or annual basis, and iii) those that report on a monthly basis report unevenly spread over time.

In this paper we investigate and compare the representativity of survey and VAT response as a function of time. The objective is to determine whether VAT is as representative as survey data and can be used to produce accurate statistics. For this purpose we use so-called Representativity (R)-indicators and partial R-indicators. The results can be used in designing data collection for monthly statistics and in assessing the timing of processing survey and register data.

Keywords: Nonresponse; R-indicators; Register

1. Introduction

Statistics Netherlands aims to replace part of its surveys by VAT data for making Short Term Statistics (STS). This should reduce the administrative burden while maintaining and possibly even increasing the quality of estimates.

In many surveys and registers, however, part of the data is missing due to non-response and time delays in reporting of enterprises to register holders. This can have a significant impact on the quality of statistics based on these data sources. The available data may not resemble the population and lead to a bias in estimates.

In this paper, we compare the quality of response of both surveys and administrative data sources. Although in the case of administrative registers missing data is due to nonreporting to the register, we will refer to this as ‘nonresponse’ as well..In Schouten, Cobben, and Bethlehem (2009), indicators for the quality of survey and register response, and their properties were developed, so-called representativity indicators or R-indicators. The indicators can be used to compare the

representativity of the response over time, and between surveys and registers. They measure the degree to which the response of a survey or register resembles the population.

Various research projects have analyzed the quality of response of survey data for STS. Hoekstra (2007) focussed on the STS survey response rates as a function of days elapsed during data collection and as a function of survey mode and timing of reminders. He concluded that response rates differ based on business size and type (economic activity). Furthermore, he noted that (paper) mail response tends to lag behind with respect to electronic response. De Nooij (2008) supplemented this research by investigating representativity of the survey data using R-indicators.

The current paper presents more extensive empirical results on the response and representativity of both STS survey and VAT data. Since VAT data should replace STS surveys (Van Delden and Aelen, 2008), we are interested in the representativity of the response at the moment statistics have to be produced and published. We, therefore, compute the representativity of the response through time, as additional survey or VAT data becomes available. We compare the representativity for both types of data and compare representativity to the response rate. Additionally, we also investigate the impact of economic activity using so-called partial R-indicators.

The indicators have been applied to social surveys before, but this article first describes an application to business surveys. It is also the first comparison between the representativity of survey and register data.

In the next section, we first discuss the general principles of R-indicators. Section 3 then presents an empirical comparison between VAT and survey data sets used for Short Term Statistics. Section 4 ends the paper with a presentation of the conclusions.

2. Indicators for representative response

If we want to describe survey or register quality in more detail, the response rate alone is not sufficient, and thus other indicators are needed. For this purpose, R-indicators and partial R-indicators were developed (Schouten et al., 2009). Since in both surveys and registers only the reporting elements are observed, it can hardly ever be established whether these are different from the nonresponding elements with respect to the target variables. Both types of indicators employ auxiliary variables from registrations or administrative data that can be linked to reporting and nonreporting units. By using auxiliary information, one can indirectly measure whether these differ. In the case of short term statistics we have the disposal of strongly related auxiliary information in the form of the previous year's VAT records and the current year's wages records.

In this section we give a short overview of R-indicators and partial R-indicators. We refer to Schouten, Cobben and Bethlehem (2009), and Shlomo et al. (2010) for more details. In sections 3 and 4 we will use the indicators in assessing response quality as a function of time.

2.1 Indicators for representative response

Two definitions of representativeness of survey response were proposed; representative response and conditional representative response. Let X and Z be two different vectors consisting of auxiliary variables, e.g. business size, VAT and economic activity.

Definition: A response to a survey is representative with respect to X when response propensities are constant for X , i.e. when $\rho_X(x)$ is a constant function.

Definition: A response to a survey is conditional representative with respect to X given Z when conditional response propensities given Z are constant for X , i.e. when $\rho_{X,Z}(x, z) = \rho_Z(z)$ for all x .

The R-indicator is defined as the transformed distance between ρ_X , the response propensity function for X , and the constant vector $\rho_0 = (\rho, \rho, \dots, \rho)^T$, which equals the response rate ρ

$$R(X) = 1 - 2S(\rho_X) \quad (2.1),$$

with $S(\rho_X)$ the standard deviation of the individual response propensities. The transformation of $S(\rho_X)$ in (2.1) was made so that $R \in [0, 1]$, and representative response, is represented by a value of one for the indicator. A value of 0 indicates the largest possible deviation from representative response. The propensity function ρ_X takes values in $[0, 1]$.

In general X will be a vector of auxiliary variables like economic activity and business size. If measuring representativeness is restricted to one auxiliary variable, say Z , then we call the indicator a partial representativeness indicator or partial R-indicator. Partial R-indicators are defined with respect to representative response and with respect to conditional representative response. In sections 2.2 and 2.3 we explain the two types of partial R-indicators.

2.2 Unconditional partial R-indicators

At the variable level the unconditional partial R-indicator is defined as

$$P_u(Z) = S(\rho_Z), \quad (2.2)$$

equal to the standard deviation of the response propensity function $\rho_Z(z)$ in the population. The subscript u in (2.2) is given in order to distinguish partial R-indicators for unconditional representative response from those for conditional representative response.

For any Z it holds that $P_u(Z) \in [0, 0.5]$. Furthermore, $P_u(Z) \in [0, (1 - R(X))/2]$ when Z is an element of X . It can be shown that when $P_u(Z) = 0$, then the response is representative with respect to Z .

Next, for categorical variables the unconditional partial R-indicators are defined for each category. Let Z be a categorical variable with categories $k = 1, 2, \dots, K$ and let Z_k be the 0-1 variable that indicates whether $Z = k$ or not. For example, Z represents business size and Z_k is the indicator for 500 or more employees. The partial R-indicator for a category k is defined as

$$P_u(Z, k) = \sqrt{\frac{N_k}{N}} (\rho_{Z_k} - \rho), \quad (2.3)$$

with N_k the number of population units in category k . In case of the example, this is the number of businesses with more than 500 employees.

We have that $P_u(Z, k) \in [-0.5, 0.5]$ and

$$P_u(Z) = \sqrt{\sum_{k=1}^K P_u^2(Z, k)}. \quad (2.4)$$

$P_u(Z, k)$ originates from dividing $P_u(Z)$ over the strata of Z while maintaining the signs between the stratum response propensity ρ_{Z_k} and the overall response rate ρ . Negative values indicate underrepresentation while positive values indicate overrepresentation. Note that (2.3), the partial R-indicator at the variable level, is in fact the square root of the “between” variance for variable Z . As such it is a component of the total variance of response propensities in (2.2), and, hence, always smaller than or equal to that variance.

2.3 Conditional partial R-indicators

In measuring conditional representativeness the impact for one variable is adjusted for the impact of other variables. At the variable level the conditional partial R-indicator is defined as

$$P_c(Z | X) = \sqrt{\frac{1}{N-1} \sum_U (\rho_{X,Z}(x_i, z_i) - \rho_X(x_i))^2}, \quad (2.5)$$

the distance between propensities based on X and Z , and based on X alone. In (2.5), $\rho_{X,Z}(x, z)$ represents the response propensity of a population unit with values $X = x$ and $Z = z$. $\rho_X(x)$ is the response propensity of a unit with value $X = x$, i.e. without any specification of the value of Z . For example, X could be a vector containing economic activity and business size while Z equals VAT in the previous reporting period.

Again it can be shown that the value of the partial indicator is always smaller than 0.5, i.e. $P_c(Z|X) \in [0, 0.5]$. A value equal to zero implies that response for Z is conditionally representative with respect to X , and, thus, a focus on X suffices.

Again, partial R-indicators for classes of categorical variables are constructed by distributing (2.5) over the classes of Z .

$$P_c(Z, k|X) = \sqrt{\frac{1}{N-1} \sum_U Z_k (\rho_{X,Z}(x_i, z_i) - \rho_X(x_i))^2}. \quad (2.6)$$

Other than for the unconditional partial indicators, it is not possible to assign a positive or negative sign to the category level conditional partial indicators in (2.6). The reason is that the sign may be different for each subclass of X . In some subclasses a certain economic activity may have a positive effect on response while in others it has a negative effect.

It can be shown that (2.5) is the square root of the “within” variance of the $\rho_{X,Z}$ propensities for a stratification of the population with X . In other words, it is the variation that is left within the cells defined by X . In our example, it represents the variation in response behaviour for VAT given its business size and type. As the within variance is again a component of the total variance, the conditional partial indicators too cannot exceed the total variance that makes up the R-indicator in (2.2). Furthermore, the conditional partial R-indicator for Z is always smaller than the unconditional partial R-indicator for that variable. This makes sense; the impact on response behaviour is to some extent removed by accounting for other characteristics of the population unit. One may assume that the impact of VAT response behaviour is completely or considerably removed by accounting for the business size or vice versa.

2.4 R-indicators and nonresponse bias

R-indicators can be interpreted in terms of the impact of nonresponse on survey estimation, as they are related to nonresponse bias through the variance of response propensities. Consider the standardized bias of the design-weighted response mean \hat{y}_r of an arbitrary survey item y .

$$\frac{|B(\hat{y}_r)|}{S(y)} = \frac{|Cov(y, \rho_Y)|}{\rho S(y)} = \frac{|Cov(y, \rho_{\mathfrak{K}})|}{\rho S(y)} \leq \frac{S(\rho_{\mathfrak{K}})}{\rho} = \frac{1 - R(\mathfrak{K})}{2\rho}, \quad (2.7)$$

with ρ the average response propensity (or expected response rate) and \mathfrak{K} some ‘super’ vector of auxiliary variables providing full explanation of nonresponse behaviour over all possible surveys.

Clearly, the propensity function $\rho_{\mathfrak{K}}$ is unknown. Since R-indicators are used for the comparison of the representativeness of response in different surveys or the same survey over time, the interest lies in the general representativeness of a survey, i.e. not the representativeness with respect to single survey items. Therefore, as an approximation for (2.7) is used

$$B_m(X) = \frac{1 - R(X)}{2\rho}. \quad (2.8)$$

B_m represents the maximal absolute standardized bias under the scenario that non-response correlates maximally to the selected auxiliary variables.

Schouten and Bethlehem (2009) and Shlomo et al (2010) proposed estimators for R , P_u , P_c and B_m . The estimators replace population means by design-weighted sample and response means and response propensities by estimated propensities. Propensities are estimated by means of general linear models like linear regression, logistic regression, or probit regression.

Schouten and Bethlehem (2009) and Schouten et al. (2010) discuss the use of the various indicators in practical settings. They also provide guidelines for the use of these indicators in comparing and monitoring response, and in changing survey design features. A useful graphical display of response rates and response representativeness is given by so-called response-representativity functions. Ideally, one would like to bound the R-indicator from below, i.e. to derive values of the R-indicator that are acceptable and values that are not. If the R-indicator would take a value below some lower bound, then measures to improve response are imperative. Response-representativity functions can be used for deriving such lower bounds for the R-indicator. They are a function of a threshold γ and the overall response rate ρ . The threshold γ represents a quality level. Here, we only regard function

$$RR_2(\gamma, \rho) = 1 - 2\rho\gamma. \quad (2.9)$$

RR_2 arises when it is demanded that the maximal bias given by (2.8) is not allowed to exceed a prescribed threshold γ . In the setting where the response quality of a single survey is evaluated, it becomes interesting to consider the estimators that are employed and the population parameters that are estimated. In many surveys the population parameters are population means or population totals. The maximal bias then gets a clear meaning; it reflects the quality of simple response means. RR_2 follows from $B_m(\rho_X) = \gamma$.

3. Comparison between VAT and survey data for STS

3.1 Background and Data

The traditional way of collecting data for business statistics is to send questionnaires to a sample of enterprises. In order to produce statistics more efficiently, less labour intensive, and with higher quality, Statistics Netherlands wants to replace part of its surveys by administrative data, particularly for small and medium sized enterprises. Apart from quality and costs, a strong incentive for the use of administrative data comes from business response burden. The use of VAT data would reduce the burden to enterprises as they do not have to provide data twice.

Business surveys are carried out in order to obtain estimates of unknown population characteristics. Also administrative data can be used to obtain these estimates. Registers are different from surveys in that they aim at a complete enumeration of a population. With this, in theory, it should be possible to make better estimates.

However, in both surveys and registers part of the data is often missing at the time Statistics Netherlands needs to produce statistics. For registers this is particularly the case for monthly statistics such as STS (Vlag and Van den Bergen, 2010). Although both are subject to missing data, the mechanisms are different. In a survey, typically not all enterprises in the sample respond to the questionnaire, or have to be prompted several times. Registers, on the other hand, may not be complete due to regulations about reporting of enterprises to register holders and time-delays in reporting.

This ‘non-response’ problem can have a significant impact on the quality of statistics based on these sources of data. The available data may not resemble the population and lead to a bias in estimates. In this section, we compare the representativeness of survey and VAT data that is used for STS statistics. The STS statistics are an important statistic, required by the European SBS requirements.

The data sets used represent turnover data for Retail trade and Manufacturing industries for 2007. The VAT register is linked to the employment register containing wages, so that these can be used as auxiliary information. About 75% of the VAT units could be linked to wages from the employment register. For the smallest enterprises (< € 2500 VAT) this was about 60%, for the larger enterprises this was at least 80%.

The VAT data uses the fiscal identity numbering (In Dutch: ‘Fi-nummer-volgnummer’), the survey uses enterprise id’s according to Statistics Netherlands’ business register (In Dutch: ‘BE-id’). For VAT, we selected all VAT units that were required to report their VAT. The sample size (for the survey data) or the number of records in the register (VAT data) for both Retail trade and Manufacturing is given in table 3.1.1.

Table 3.1.1: Sample and register size

	<i>Retail trade</i>		<i>Manufacturing</i>	
	<i>VAT</i>	<i>Survey</i>	<i>VAT</i>	<i>Survey</i>
January	124602	7852	59346	5393
June	126158	7871	60229	5381
July	127568	7727	61023	5355
December	128212	7864	61521	5078

The VAT data includes records for companies reporting on a monthly, quarterly or annual basis. The reporting frequency depends on the amount of VAT a company is expected to report, or based on individual requirements made by the tax authorities.

If the VAT of a company lies below €1883 per year, they can report on an annual basis, if it exceeds €15000 per quarter, they should report on a monthly basis. Most companies report on a quarterly basis (Slootbeek and Van Bommel, 2010).

For STS survey data, there are (sub)industries that are included in a survey only on a monthly or quarterly basis. However, for Retail trade and Manufacturing, all companies take part in monthly surveys only, thereby eliminating the need to redistribute quarterly data over three months.

In the case of the VAT register, companies are required to report 25 days after a reporting period has ended, and statistics are produced 30 days after that period. However, not all companies have reported within 30 days. For the STS survey, companies are given a deadline for responding, after which several fieldwork strategies are employed to increase response. The initial survey is sent using one of three modes: a paper questionnaire sent by mail, an invitation via e-mail to fill out the web-based survey, or an invitation sent out by regular mail to fill out the web-based survey.

3.2 Setup of computations

The comparison was done for four different months with distinct characteristics of VAT data: January, June, July and December. The data for January includes only companies reporting on a monthly basis. In June, we have companies reporting on a monthly and on a quarterly basis. July, again, only includes companies reporting on a monthly basis, but unlike January is not at the beginning of the year. December includes companies reporting on monthly, quarterly, and annual basis.

Ideally, we would like to compare the R-indicators for both types of data using the same auxiliary variables. However, for the VAT and survey data sets the same auxiliary variables are not available. This is caused by the difference in population frames as used by Statistics Netherlands and the Tax Authority. For VAT data, we can use the current year's monthly wages records, the previous year's VAT records (for the same month), and a business classification (enterprise groups according to NACE classification of 1974). For survey data we can use business size, business classification (economic activity according to NACE classification of 1993) and VAT of the previous year (for the same month). The current year's wages resemble the business size. The business size is a classification of the number of employees which can be expected to be proportional to the wages. It is, however, not the same variable so that a direct comparison is hampered. The two business classifications also show resemblance but are not the same. It should also be noted that the STS statistics are published at a different level than the business classification we use here. Publication levels are cross sections of certain business sizes and enterprise groups.

A second difference between the data sets is the units for which the response is recorded. Results for the VAT register and survey data can thus not be compared

directly. However, this only means the absolute values of the R-indicator cannot be compared. We can compare the relative values through time (or pattern), though.

For both Retail trade and Manufacturing we tested two models based on the VAT register, and two models based on STS survey data. See table 3.2.1 for an overview of the models.

All auxiliary variables were categorized into distinct categories. See Appendix 2 for a description of the categories of VAT and Wages. Table 3.2.2 presents an overview of the variables and numbers of categories used.

Table 3.2.1: Models used for the estimation of response propensities

<i>Model</i>	<i>Data set used</i>	<i>Auxiliary data</i>
Model 1	VAT-register	VAT(t-12) wages(t)
Model 2	VAT-register	VAT (t-12) wages (t) NACE-3 digit (1974)
Model 3	STS survey data	Business size x VAT(t-12)
Model 4	STS survey data	NACE-3digit (1993) Business size x VAT(t-12)

Table 3.2.2: Number of categories per variables

<i>Variable</i>	<i># categories</i>
VAT(t-12)	9 categories
Wages(t)	10 categories
Business size	9 categories
NACE 3-digit (1993) Manufacturing	100 categories
Retail trade	7 categories
Business size x VAT(t-12)	90 categories
NACE 3-digit (1974) Manufacturing	182 categories
Retail trade	18 categories

Since VAT data should replace surveys, we compute the representativity of the response through time, as additional survey or VAT data becomes available. We

compare the representativity for both types of data and compare representativity to the response rate. Since companies are required to report 25 days after a reporting period has ended, and statistics are produced 30 days after that period, we computed both response rate and R-indicator after 25, 26, 27, 28, 29, 30, and 60 days after a reporting period had finished.

In the next section we first compare the results for models 1 and 3, i.e. a model for VAT data and one for survey data. In Section 4 we also add models 2 and 4 to the comparison, so that we see the effect of adding business classification to the models.

3.3 Results for VAT vs. survey response

In this section we focus on the following questions:

1. Does representativity change during data collection, and specifically between 25 and 30 days after the end of the reference month?
2. Does representativity differ between various months of the year?
3. Are results different for Manufacturing and Retail trade?
4. How does the representativity of response compare between survey and register data?

In the discussion, we present a selection of graphs to illustrate the results. Some graphs were omitted in the text as they present similar pictures. These graphs can be found in Appendix 1. In all graphs indicators are computed after 25, 26, 27, 28, 29, 30 and 60 days of data collection. The different time points are equally spaced in the plot, but the values for 60 days correspond to an additional 30 days of data collection.

3.3.1 Representativity during data collection

We first present the response rate and R-indicator for Retail trade using Model 1 and Model 3. Figure 3.3.1 and Figure 3.3.2 show results for the respective models for January, June, July and December 2007. For VAT, the response rate is the number of units that have reported VAT as a proportion of all units in the register (i.e. units that should report their VAT). For survey data, the response rate is the proportion of units in the sample that have responded.

Figure 3.3.3 presents the response as a proportion of total turnover. For VAT, the proportions are calculated as the sum of turnovers of reporting units divided by turnover of all units in the register. For Survey data the proportions are calculated as the sum of turnovers of responding units divided by turnover of all units in the sample. It should be noted that the sample is not representative of the population, i.e. it contains a relative significant number of large companies.

When we look at these figures, we see that for both model 1 and model 3, and all four months under investigation, the response rate increases as the data collection period progresses. The increase is stable for the STS survey. However, for VAT the response increase differs considerably over the months due to the inclusion of

quarterly and annual reporters. The response patterns for VAT in January and July are quite similar. Since these consist only of monthly reporters, both represent the results for that group. Likewise, the patterns for July and December are similar, since these also include quarterly reporters.

Figure 3.3.1: Response rate and R-indicator based on VAT data for Retail trade (Model 1), for January, June, July and December 2007.

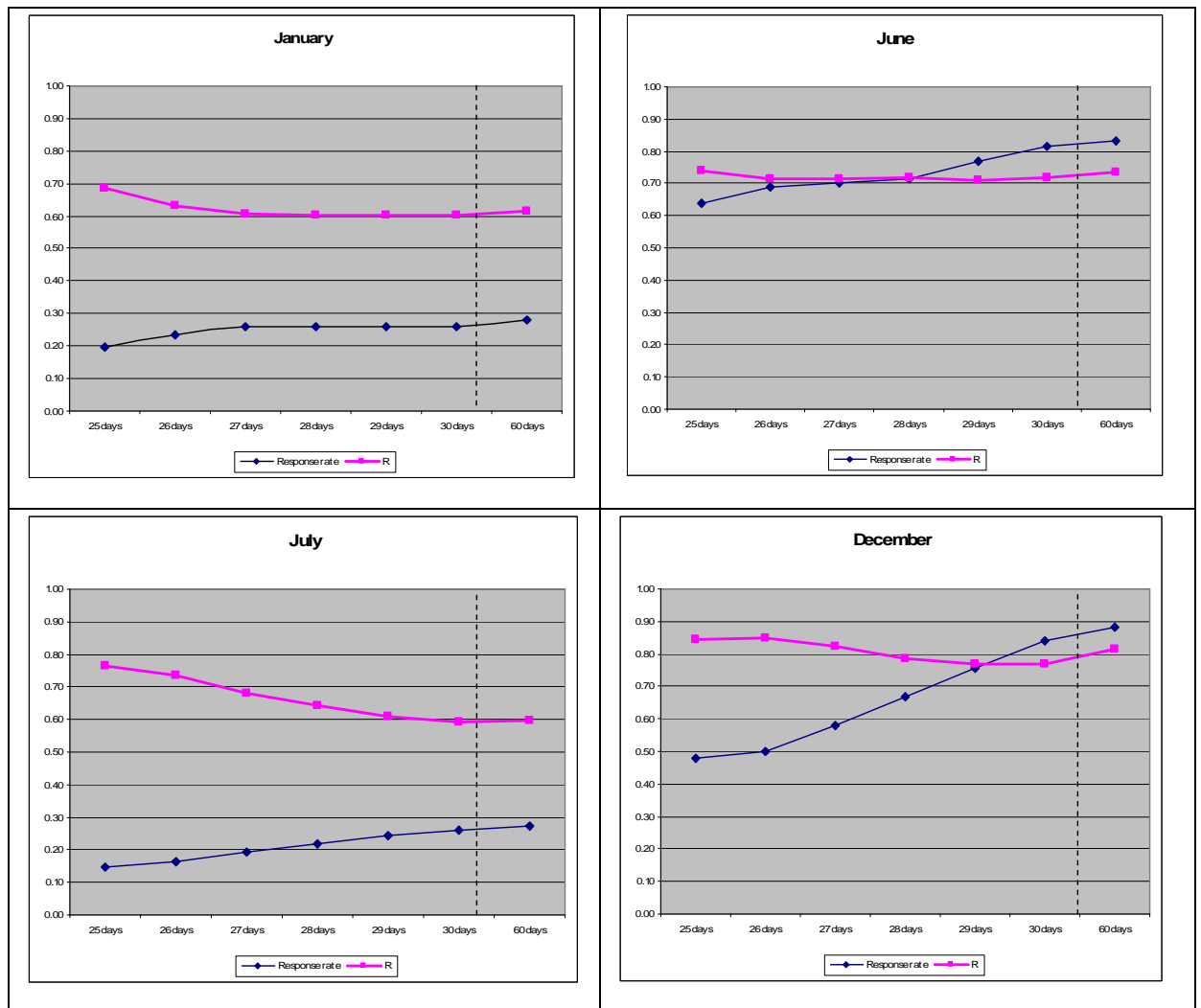


Figure 3.3.2: Response rate and R-indicator based on survey data for Retail trade (Model 3), for January, June, July and December 2007.

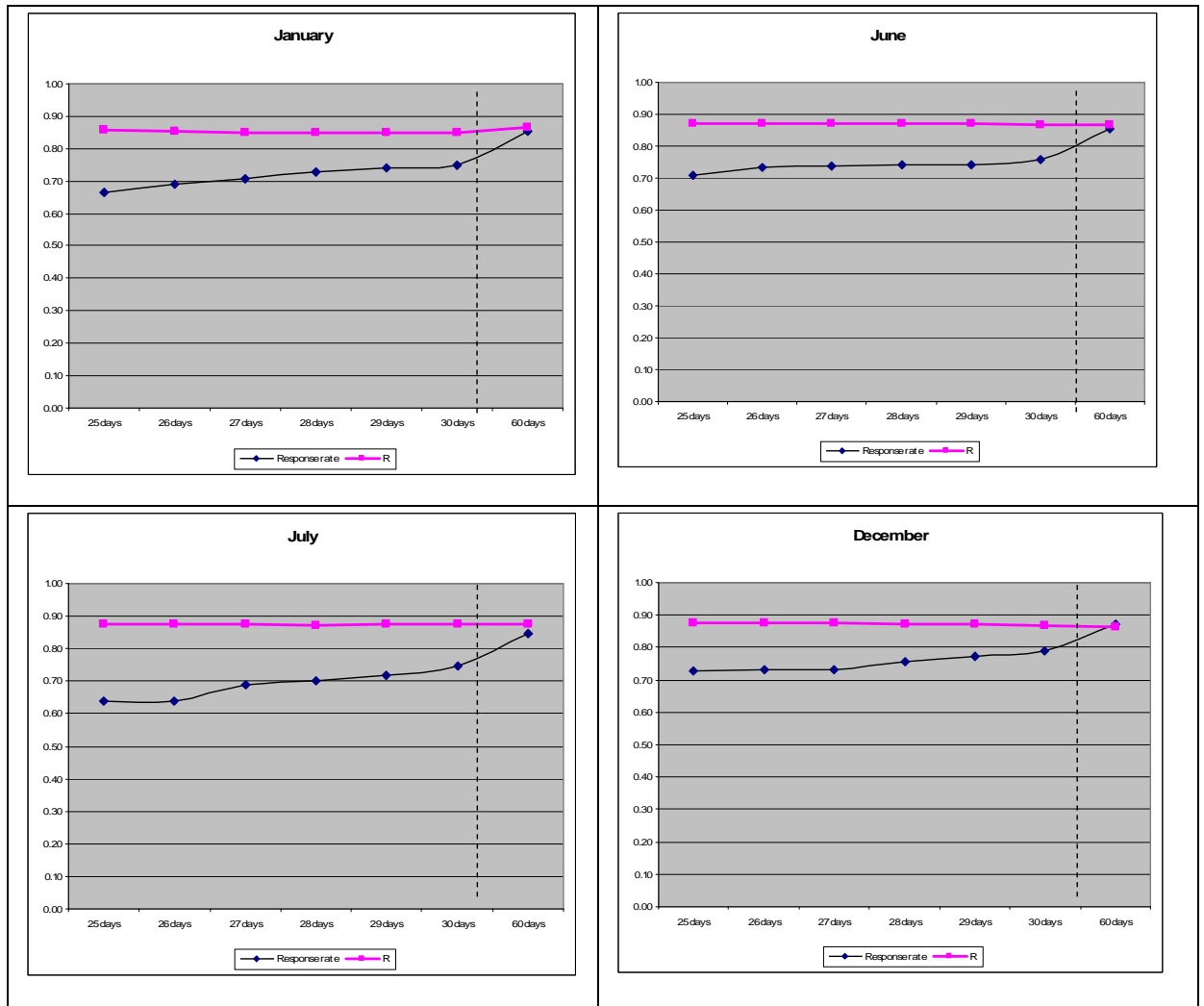
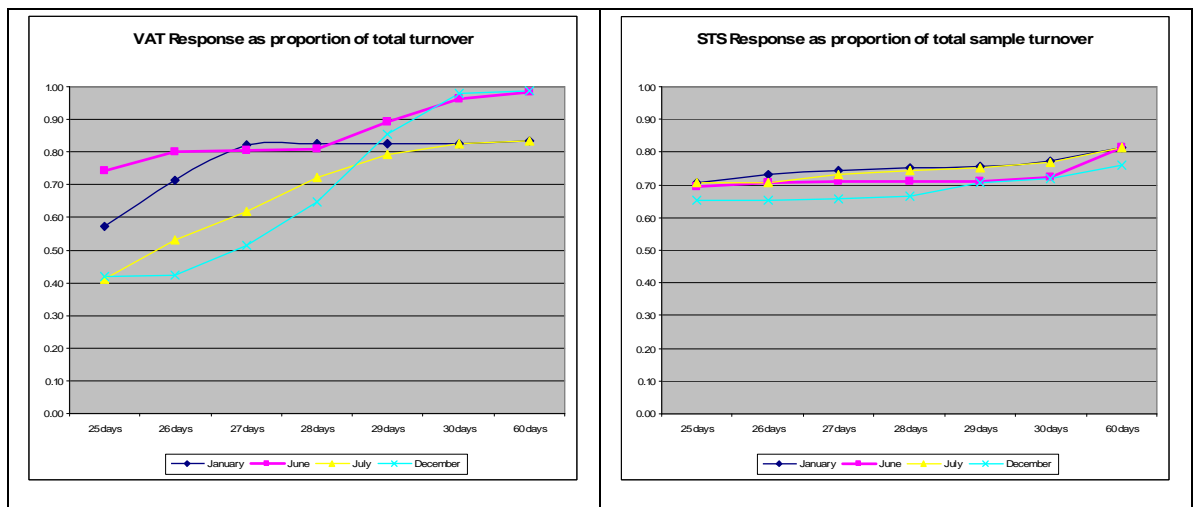


Figure 3.3.3: Reponse as a proportion of total turnover, for Retail trade VAT and Survey data.



The representativity patterns of the response are not in line with the response rate patterns: it may change only slightly as the response rate increases, or may even decline. For STS survey response the R-indicator is stable. The picture for the VAT response is clearly different. Generally, the R-indicators drop as data collection proceeds and there is only a mild increase after 30 days of data collection. We conclude that the contrast between reporting and non-reporting units increases. The additional response between 25 and 30 days is thus not as representative of the population as the initial response. Note that in the end, after more than 60 days, the R-indicator should go to 1, when all data is available. This is not the case for any of the VAT periods studied, since response rate never reaches 100%.

Hence, waiting longer than 25 days before producing statistics based on VAT data does not make the data more representative. Publishing based on data collected at 25 days after the reporting period seems viable, therefore. Of course a higher response rate would still imply a higher precision and, consequently, smaller margins of error. Since this is not the focus of this paper, we ignore precision, although this makes sense as registers contain a full enumeration of the target population. The importance of correction for selective nonresponse, e.g. using multiplicative or linear weighting, remains important, however. For VAT data this is even more important than for survey data. In a survey the selected sample to a large extent determines the representativity of the data. In VAT data, on the other hand, external factors such as the tax law determine which companies have to report, so that representativity can not be influenced.

3.3.2 Representativity from month to month

If we compare the four months for Retail trade for VAT data in Figure 3.3.1, we see the following:

- In January we have only monthly reporters, so the response rate is low, and the data in the register is not very representative
- In June there are also quarterly reporters, leading to a higher response rate. It also makes the response more representative
- July again is the first month of a quarter, so the response rate is low and data is not very representative. January and July show a similar trend.
- In December we have monthly, quarterly and yearly reporters, leading to the highest response rate, and the most representative data.

For the survey data, the difference between the four months is only small. As mentioned, in our dataset we only have companies taking part in surveys on a monthly basis. Only in July the response rate is slightly lower than in other months, which may be due to seasonal effects in Retail trade, such as holidays. Representativity however is not different from other months.

3.3.3 Difference between Manufacturing and Retail trade

In Figure 3.3.4 and Figure 3.3.5 the results for Manufacturing based on VAT (Model 1) and survey data (Model 3) can be found. Figure 3.3.6 adds the response turnover proportions. It follows that, although the levels of response and representativity may differ, there is little overall difference with results for Retail trade and so here the same conclusions apply as for Retail trade. The patterns for the R-indicator values are similar: STS survey response shows a stable picture and VAT response has decreasing R-indicators with patterns that are considerably different over the four months.

In section 3.4 we will see that the individual impact of the auxiliary variables is, however, different between Retail trade and Manufacturing.

Figure 3.3.4: Response rate and R-indicator based on VAT data for Manufacturing (Model 1), for January, June, July and December 2007.

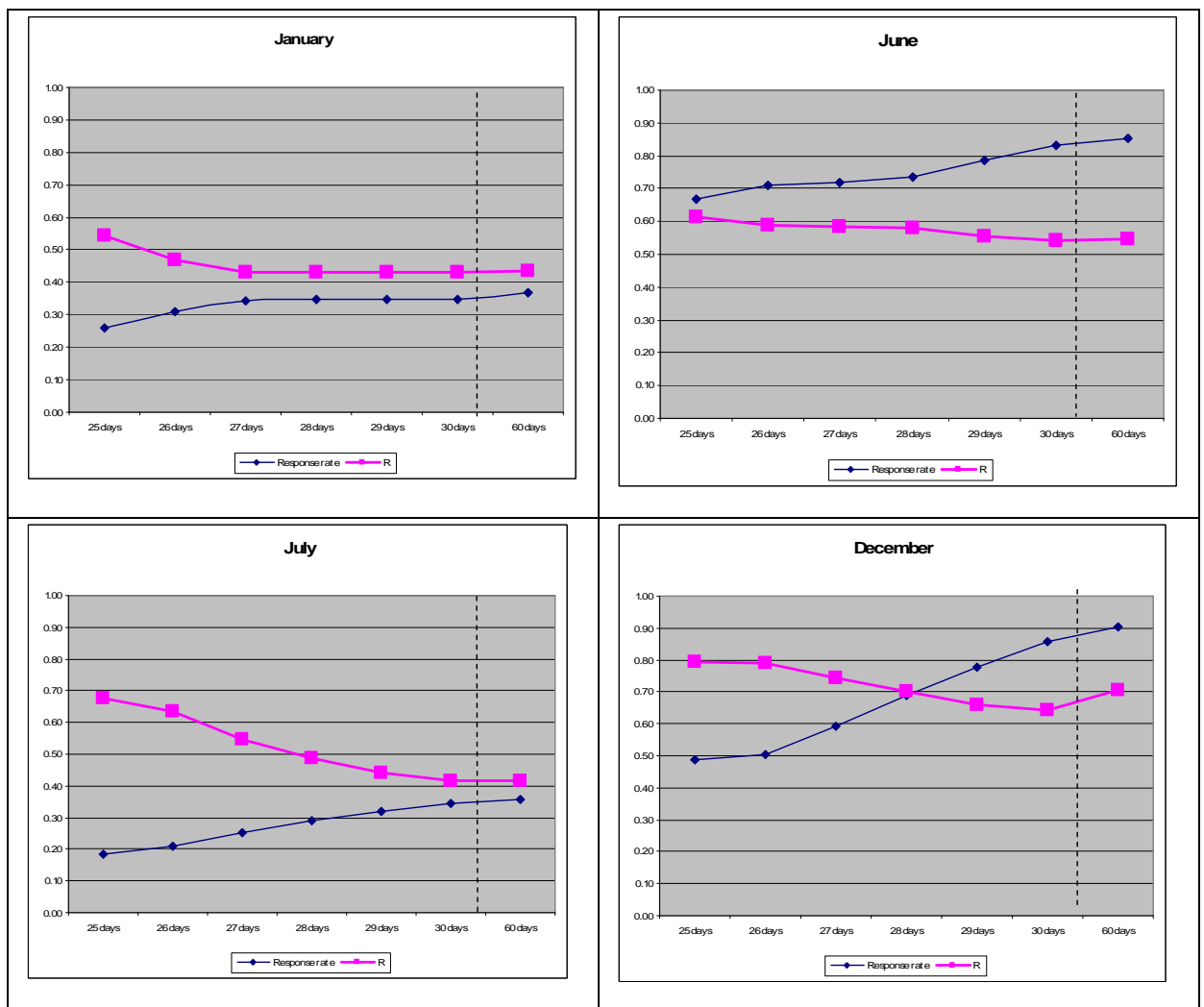


Figure 3.3.5: Response rate and R-indicator based on survey data for Manufacturing (Model 3), for January, June, July and December 2007.

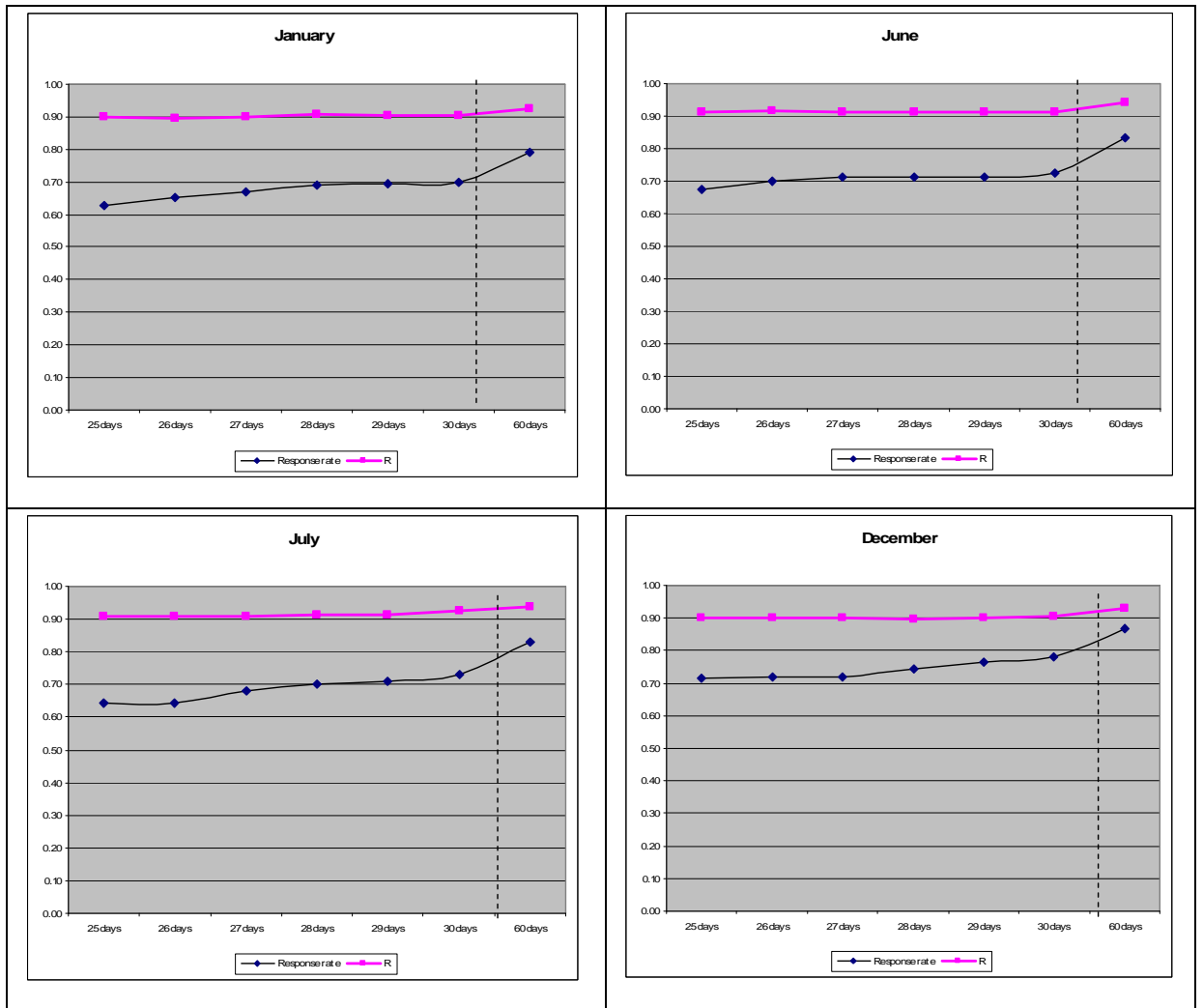


Figure 3.3.6: Reponse as a proportion of total turnover, for Manufacturing VAT and Survey data.



3.3.4 *Survey versus register*

The main difference between representativeness of response to surveys and to register holders is the stability over time and during data collection. For the STS survey, the R-indicator remains more or less the same during data collection, despite the increase in response rate. Between 25 and 30 days representativity hardly changes; only after 30 days there is a slight increase. For the register, representativity changes considerably over time, and actually goes down as more data becomes available. The most striking difference is, however, the stability over months. Between the various months there is again little difference for the STS survey. The VAT data shows considerable variation and the representativity of response in months without quarterly and annual reporters is much lower than for the other months.

We may, therefore, conclude that for VAT data there must be a stronger reliance on nonresponse adjustment methods in months with only monthly reporters and, equally important, that comparability over months is weaker. We must remark that we restricted ourselves to nonresponse error and ignored other influential errors like measurement error and sampling error. Register data will produce smaller sampling errors and may also be less prone to measurement error.

Figures 3.3.7 and 3.3.8 show response-representativity functions for VAT and survey data for Retail trade. The straight lines in the plots represent so-called maximal bias levels. From the top to bottom they represent values of 0.1, 0.2, ... 0.8. The steeper the line, the bigger the maximal bias level. Ideally, response should end up at the upper right corner of the response-representativity function, i.e. a high response rate and a high R-indicator. The maximal bias can be interpreted as a worst-case bias that arises when a survey target variable correlates maximally to nonresponse.

The plots in figures 3.3.7 and 3.3.8 confirm the previous analyses. The STS survey data shows stable patterns over the months. During data collection the maximal bias level remains almost constant. For the VAT data, however, the maximal bias levels vary considerably over the months. Periods with only monthly reporters have a higher maximum bias than other periods.

In Appendix 1, the response-representativity plots for Manufacturing can be found. These are similar to the plots here, although for Model 1 the maximum bias levels are slightly higher for Manufacturing than for Retail trade, and for Model 3, they are slightly lower.

Figure 3.3.7: RR2, based on VAT data for Retail trade (Model 1), for January, June, July and December 2007.

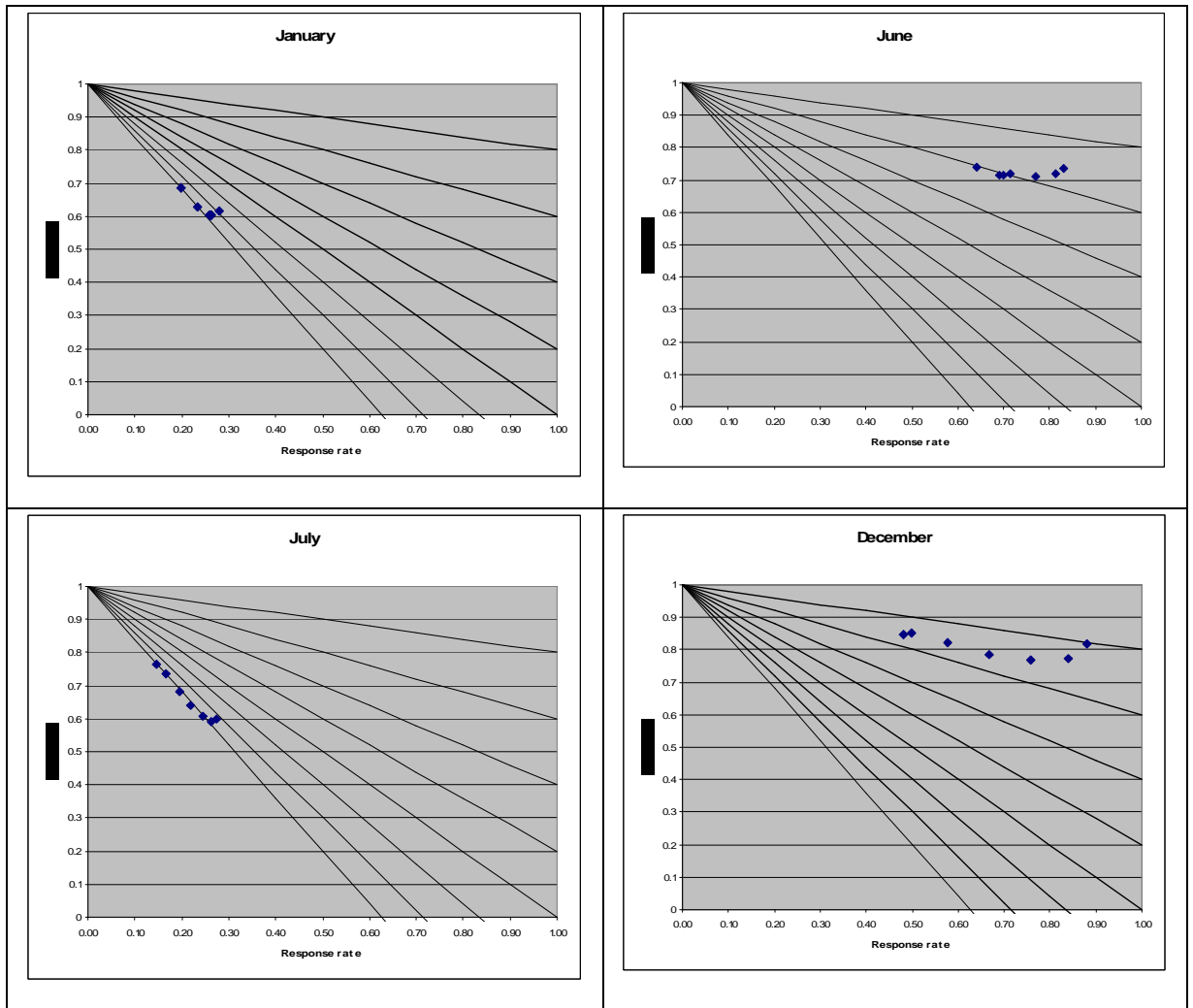
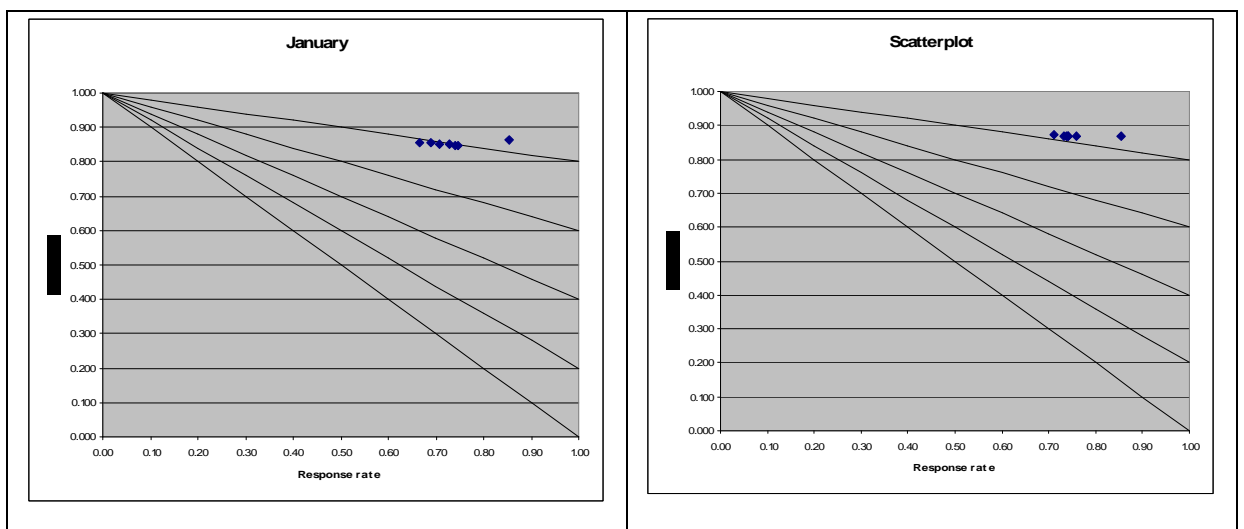
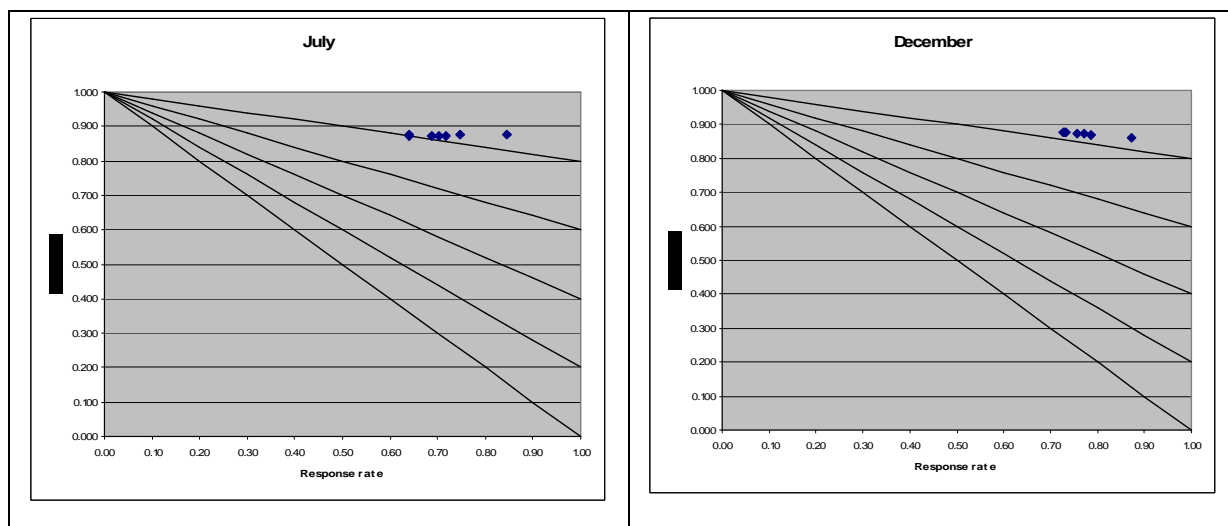


Figure 3.3.8: RR2, based on survey data Retail trade (Model 3), for January, June, July and December 2007.





4. The impact of single enterprise characteristics on representative response

The main question we would like to answer in this section is what characteristics impact representativity of response most strongly. Furthermore, we want to know whether this impact changes during data collection and whether there are differences between STS-survey and VAT-response.

In order to widen the scope of our analysis, we have included economic activity as an auxiliary variable for both STS survey data and VAT data, resulting in models 2 and 4 (see Section 3.2). The representativity and representativity-reponse plots for the extended models can be found in Appendix 1 (Retail trade, model 2, and Manufacturing, model 4). For Retail trade, the plots for model 4 were virtually identical to those of model 3 (without economic activity), while for Manufacturing, the plots for model 2 were almost identical to those for model 1. These plots are therefore not included. For Retail trade, model 2 (VAT) gives a very slightly lower value of the R-indicator. For model 4, Manufacturing gives a slightly smaller R-indicator as well.

Schouten et al. (2010) present guidelines for the use of R-indicators and partial R-indicators for monitoring data collection, according to the following steps:

1. Assess the unconditional variable-level partial R-indicators for all auxiliary variables; the variables that have the highest scores have the strongest single impact on representativity of response. They are also the strongest candidates to be monitored and analyzed more closely and subsequently to be involved in design changes and data collection interventions
2. Assess the conditional variable-level partial R-indicators for all auxiliary variables; the conditional values are needed in order to check whether some of the variables are strongly collinear. If indicator scores remain high then the strongest variables are selected. If indicator scores vanish by

conditioning, then it is sufficient to focus only on a subset of the variables. A low conditional indicator value implies that the corresponding variable is conditionally representative.

3. Repeat steps 1 and 2 but now for the category-level partial R-indicators and for the selected auxiliary variables only; the subgroups that need to be targeted in design changes are those categories that have large negative unconditional scores and large conditional scores. Recall that conditional category-level partial R-indicators do not have a sign and are always positive.

In the following sections we will follow the three steps for the STS and VAT data sets.

4.1 Partial R-indicators for the VAT data and STS survey data

The first step is an evaluation of the variable-level partial R-indicators for VAT data and STS survey data given by (2.2) and (2.5).

Tables 4.1.1 to 4.1.4 present the variable-level unconditional and conditional partial R-indicators after 25 days of data collection for STS survey and VAT data for Retail trade and Manufacturing. The unconditional variable-level indicators are given for all variables in models 2 (STS) and 4 (VAT). The conditional variable-level indicators for the STS survey are given only for economic activity. We do not provide the conditional partial indicators for reported VAT in the previous year and business size as these two variables are crossed in the models for the estimation of response propensities. As a consequence, it is not possible to disentangle the impact of these two variables. The conditional indicators follow from conditioning on the other variables in the model. For example, the VAT conditional indicators for economic activity arises from conditioning on wages (t) and VAT (t-12).

Table 4.1.1: Unconditional and conditional partial R-indicators for VAT Retail trade after 25 days of data collection.

		<i>Partial R-indicators</i>	
		<i>Unconditional</i>	<i>Conditional</i>
Economic activity	January	0.0739	0.0780
	June	0.0426	0.0326
	July	0.0534	0.0525
	December	0.0265	0.0197
Wages (t)	January	0.1096	0.0455
	June	0.0754	0.0204
	July	0.0760	0.0313
	December	0.0449	0.0178
VAT (t-12)	January	0.1522	0.1086
	June	0.1292	0.1046
	July	0.1137	0.0872
	December	0.0748	0.0613

Table 4.1.2: Unconditional and conditional partial R-indicators for VAT Manufacturing after 25 days of data collection.

		<i>Partial R-indicators</i>	
		<i>Unconditional</i>	<i>Conditional</i>
Economic activity	January	0.0962	0.0464
	June	0.0755	0.0417
	July	0.0698	0.0315
	December	0.0486	0.0365
Wages (t)	January	0.0811	0.0331
	June	0.1728	0.1363
	July	0.0513	0.0221
	December	0.0942	0.0773
VAT (t-12)	January	0.2249	0.1953
	June	0.1326	0.0788
	July	0.1591	0.1400
	December	0.0637	0.0370

Table 4.1.3: Unconditional and conditional partial R-indicators for STS Retail trade survey after 25 days of data collection.

		<i>Partial R-indicators</i>	
		<i>Unconditional</i>	<i>Conditional</i>
Economic activity	January	0.0317	0.0273
	June	0.0337	0.0295
	July	0.0280	0.0279
	December	0.0313	0.0249
Business size	January	0.0238	
	June	0.0289	
	July	0.0185	
	December	0.0352	
VAT (t-12)	January	0.0554	
	June	0.0489	
	July	0.0396	
	December	0.0420	

Table 4.1.4: Unconditional and conditional partial R-indicators for STS Manufacturing survey after 25 days of data collection.

		<i>Partial R-indicators</i>	
		<i>Unconditional</i>	<i>Conditional</i>
Economic activity	January	0.0814	0.0782
	June	0.0769	0.0748
	July	0.0817	0.0775
	December	0.0780	0.0744
Business size	January	0.0335	
	June	0.0306	
	July	0.0353	
	December	0.0360	
VAT (t-12)	January	0.0267	
	June	0.0171	
	July	0.0196	
	December	0.0249	

Based on tables 4.1.1 – 4.1.4 we make the following observations:

- The unconditional and conditional indicator values for economic activity are almost similar in size for both STS survey response and VAT Retail trade. However, for VAT Manufacturing the impact of economic activity is attenuated by wage and reported VAT
- For the STS Manufacturing survey the economic activity produces the largest unconditional indicator values and dominates business size and reported VAT.
- For the STS Retail trade survey the variable-level indicators are similar in size for all variables and relatively small.
- For VAT Retail trade the reported VAT of previous year has the largest variable-level indicator values and produces the strongest impact on representative response.
- For VAT Manufacturing the reported VAT leads to the largest indicator values for January and July. In June and December the largest values come from the reported wages.
- For VAT response partial indicators vary considerably more than for STS survey response over the various months.

The first observation implies that the impact of economic activity is almost orthogonal to the impact of business size or wage and reported VAT for STS-survey response and for VAT-Retail trade. In other words, economic activity affects response representativity of both large and small businesses in terms of number of employees and turnover for STS and for Retail trade VAT. Hence, efforts to increase

representativity of response with respect to economic activity may be applied regardless of business size or turnover.

We further investigate the impact of reported VAT and wages for the VAT data and economic activity for the STS Manufacturing survey data in sections 4.2 and 4.3, respectively. Since the variable-level indicator values for STS Retail trade data are small, we do not further investigate this data set.

4.2 The impact of reported VAT in previous year and wages on VAT data

In this section we elaborate our investigation into the impact of VAT (t-12) on VAT Retail trade data, and the impact of VAT (t-12) and Wages (t) on VAT Manufacturing data. For this purpose we employ the category-level partial R-indicators given by (2.3) and (2.6).

Table 4.2.1 shows the category-level partial R-indicators for VAT (t-12) for VAT Retail trade after 25 days of data collection. Indicator values (not shown) indicate that the impact is stable when the number of days of data collection increases. For this reason, we restrict ourselves to an analysis of the indicator values after 25 days. However, it is important to realise that the same business subpopulations remain to impact representative response for VAT Retail trade.

From table 4.2.1 we conclude that there are two subgroups that always impact representativeness negatively: businesses that reported a VAT below 2,500 Euros and business that were non-existent in the previous year. The impact of the two subgroups is similar. Additionally in the months January and July the businesses with reported VAT between 2,500 and 10,000 Euros have a strong negative impact. In the months June and December these businesses, however, perform similarly to the businesses with a larger reported VAT. This result is not surprising given that January and July do not include the quarterly and annual reporters and the reporting frequency is based on expected VAT thresholds.

Table 4.2.1: Category-level partial R-indicators for VAT (t-12) calculated for VAT Retail trade. Categories are given in thousands of Euros.

Category	January		June		July		December	
	P_u	P_c	P_u	P_c	P_u	P_c	P_u	P_c
<2.5	-0.045	0.032	-0.087	0.066	-0.032	0.022	-0.048	0.035
2.5 - 10	-0.046	0.031	0.014	0.030	-0.036	0.026	0.013	0.022
10-20	-0.008	0.014	0.031	0.033	-0.009	0.012	0.020	0.020
20-30	0.020	0.019	0.033	0.026	0.010	0.011	0.023	0.018
30-50	0.044	0.030	0.041	0.028	0.029	0.020	0.026	0.018
50-100	0.070	0.047	0.036	0.023	0.052	0.036	0.022	0.013
100-200	0.064	0.044	0.033	0.023	0.051	0.037	0.013	0.008
>200	0.081	0.063	0.035	0.026	0.061	0.049	0.011	0.007
No VAT	-0.034	0.036	-0.040	0.039	-0.025	0.027	-0.028	0.026

Table 4.2.2: Category-level partial R-indicators for VAT (t-12) calculated for VAT Manufacturing of January. Categories are given in thousands of Euros.

Category		25 days	26 days	27 days	28 days	29 days	30 days	60 days
<2.5	Pu	-0.079	-0.093	-0.100	-0.100	-0.100	-0.100	-0.098
	Pc	0.069	0.082	0.087	0.087	0.087	0.087	0.084
2.5-10	Pu	-0.071	-0.084	-0.090	-0.090	-0.091	-0.091	-0.093
	Pc	0.075	0.088	0.095	0.096	0.096	0.096	0.098
10-20	Pu	-0.007	-0.008	-0.007	-0.007	-0.007	-0.007	-0.009
	Pc	0.002	0.003	0.003	0.003	0.003	0.003	0.003
20-30	Pu	0.030	0.036	0.039	0.039	0.039	0.039	0.038
	Pc	0.028	0.033	0.036	0.036	0.036	0.036	0.035
30-50	Pu	0.059	0.069	0.074	0.074	0.074	0.074	0.073
	Pc	0.053	0.062	0.066	0.066	0.066	0.066	0.065
50-100	Pu	0.093	0.105	0.112	0.112	0.112	0.112	0.110
	Pc	0.081	0.091	0.097	0.098	0.098	0.098	0.095
100-200	Pu	0.089	0.103	0.108	0.109	0.109	0.109	0.107
	Pc	0.075	0.087	0.091	0.091	0.091	0.091	0.089
>200	Pu	0.127	0.151	0.161	0.161	0.162	0.161	0.160
	Pc	0.099	0.119	0.126	0.126	0.126	0.126	0.125
No VAT	Pu	-0.047	-0.053	-0.057	-0.057	-0.057	-0.057	-0.052
	Pc	0.040	0.046	0.048	0.048	0.048	0.048	0.043

Table 4.2.2 contains the category-level partial R-indicators for reported VAT in previous year for VAT Manufacturing. The values given are for the month January, but similar values are found for July. Since the indicator values change as data collection approaches, the values are given as a function of number of days of data collection.

The indicator values in table 4.2.2 suggest that the businesses with a VAT (t-12) below 20,000 Euros and businesses that were not active in the previous year have a negative impact on representative response. The impact for businesses with reported VAT (t-12) between 10,000 and 20,000 Euros is relatively weak. Generally, it follows that the impact of businesses without VAT (t-12) remains stable over time, but the impact of the businesses with VAT (t-12) below 20,000 Euros increases with time. Hence, the representation of these businesses gets worse when data collection proceeds.

Table 4.2.3 presents the indicator values for Wages (t) for VAT Manufacturing data in June. The results for December are not shown, but have exactly the same patterns. The indicator values for December, however, are less extreme, i.e. underrepresentation and overrepresentation is smaller for all groups.

Table 4.2.3: Category-level partial R-indicators for Wages (t) calculated for VAT Manufacturing of June. Categories are given in thousands of Euros.

Category		25 days	26 days	27 days	28 days	29 days	30 days	60 days
<=0	Pu	0.034	0.038	0.038	0.038	0.041	0.044	0.044
	Pc	0.032	0.035	0.035	0.036	0.039	0.043	0.043
0-2,5	Pu	0.025	0.025	0.026	0.028	0.030	0.031	0.031
	Pc	0.026	0.026	0.027	0.029	0.031	0.032	0.033
2,5-10	Pu	0.037	0.039	0.040	0.041	0.045	0.047	0.049
	Pc	0.034	0.036	0.037	0.039	0.043	0.046	0.047
10-20	Pu	0.023	0.026	0.027	0.028	0.030	0.032	0.033
	Pc	0.021	0.024	0.025	0.026	0.028	0.031	0.032
20-30	Pu	0.019	0.020	0.021	0.021	0.022	0.024	0.023
	Pc	0.017	0.017	0.018	0.019	0.020	0.021	0.021
30-50	Pu	0.018	0.020	0.020	0.022	0.022	0.023	0.023
	Pc	0.017	0.018	0.019	0.020	0.021	0.022	0.023
50-100	Pu	0.024	0.023	0.024	0.023	0.024	0.026	0.025
	Pc	0.021	0.021	0.022	0.021	0.022	0.025	0.024
>100	Pu	0.030	0.031	0.031	0.032	0.030	0.031	0.030
	Pc	0.025	0.026	0.026	0.027	0.026	0.027	0.027
Nonresponse to register	Pu	0.041	0.043	0.044	0.044	0.048	0.049	0.049
	Pc	0.034	0.036	0.037	0.038	0.041	0.044	0.045
No link to register	Pu	-0.150	-0.158	-0.161	-0.165	-0.176	-0.185	-0.185
	Pc	0.112	0.119	0.122	0.126	0.136	0.145	0.148

From the results in table 4.2.3 we conclude that there is a single subgroup that negatively and strongly affects representativeness of response: businesses for which no wages were reported. This result is somewhat surprising at first sight as the reported wages refer to the month of the VAT data collection period. Hence, when VAT is reported one would also expect wages to be reported. However, this finding becomes less surprising when it is realised that businesses need not report wages and VAT on the same fiscal unit. Some businesses use different units. Linking the wages and VAT on different fiscal units is complicated as one needs to have insight in the overall business structure. Furthermore, wages may be reported for multiple businesses in the VAT data or vice versa, i.e. there does not have to be a one to one link. Apparently, such fiscal units do not report VAT or are very slow responders when it comes to VAT.

Summarising we can state that for VAT data mostly small and new businesses affect representativeness in a negative way. For VAT Manufacturing data in July and December we find that businesses that report wages and VAT on different fiscal units perform very badly. Since December VAT data collection involves monthly, quarterly and annual reporters, the latter finding is remarkable.

4.3 The impact of economic activity on STS Manufacturing survey data

In this section we elaborate our investigation into the impact of economic activity on STS Manufacturing survey data. For this purpose we again employ the category-level partial R-indicators given by (2.3) and (2.6).

We first analyse the dependence on the number of data collection days. Table 4.3.1 presents the variable-level partial R-indicators for the STS Manufacturing survey as a function of number of data collection days. The indicator values show that both elapsed number of days and season do not strongly influence representativity of response due to economic activity. The indicators have a stable value across months and days and decrease only slightly between 30 and 60 days of data collection. This period, however, falls after the processing of the response data. This finding suggests that measures taken to improve response may be effective regardless of time and season.

Table 4.3.1: Unconditional partial R-indicators for STS Manufacturing survey as a function of time.

	<i>January</i>	<i>June</i>	<i>July</i>	<i>December</i>
25 days	0.0814	0.0769	0.0817	0.0780
26 days	0.0786	0.0722	0.0817	0.0772
27 days	0.0764	0.0721	0.0790	0.0776
28 days	0.0725	0.0719	0.0742	0.0736
29 days	0.0715	0.0722	0.0740	0.0683
30 days	0.0712	0.0708	0.0698	0.0681
60 days	0.0676	0.0575	0.0601	0.0627

Next, we zoom in on the category-level partial R-indicators for the STS Manufacturing survey. Since there is no clear dependence on time, we restrict ourselves to response after 25 days of data collection. Figures 4.3.1 to 4.3.4 plot the unconditional and conditional category level partial R-indicators for type of business for January, June, July and December.

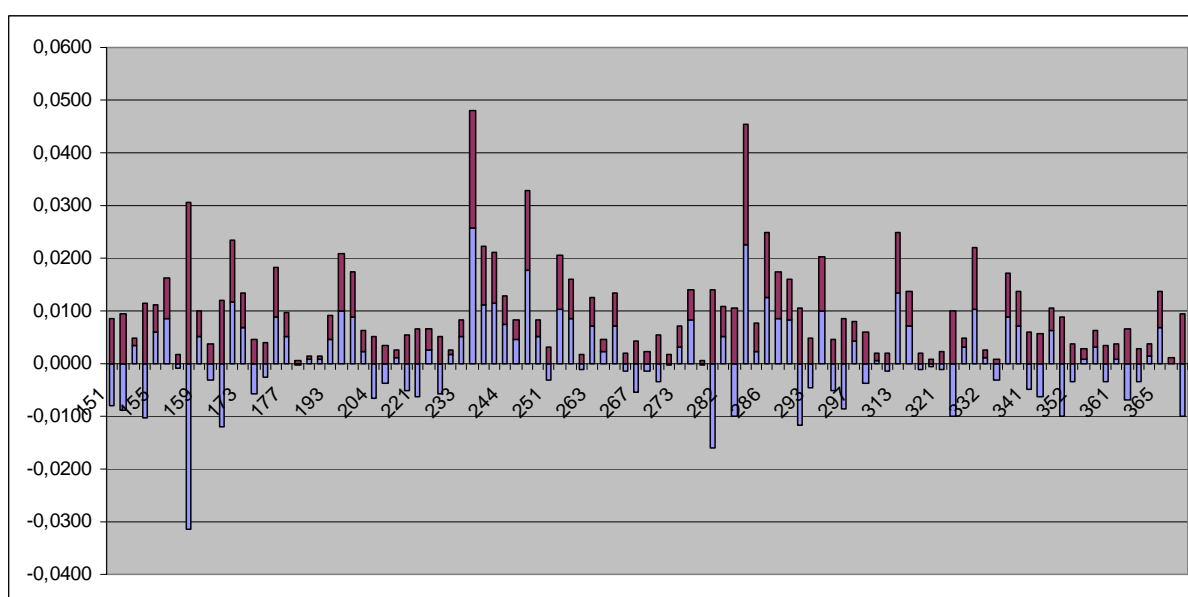
Contrary to subgroup response rates, category-level partial R-indicators account for the size of subpopulations. Hence, partial R-indicator values are close to zero whenever the corresponding subgroup is small. Negative unconditional values imply underrepresented groups and positive unconditional values imply overrepresented groups. Business for which the unconditional value is strongly negative and for which the conditional value is large, are businesses that are interesting for response enhancing measures.

From figure 4.3.1 to 4.3.4 we conclude that there is a small number of economic activities that have large negative unconditional values and large conditional values. Table 4.3.2 contains these categories for the four months. The strongest and most consistent impact on representativity of response comes from NACE 158 and NACE 281.

Table 4.3.2: Economic activities that have large negative category-level unconditional and large conditional partial indicator values.¹

NACE	January	June	July	December
152		X	X	
155		X		X
158	X	X	X	
171	X	X	X	
174		X		
204				X
281	X	X	X	X
283			X	
292	X			
294		X		
333		X	X	
342			X	X
351				X

Figure 4.3.1: Unconditional (blue) and conditional (pink) category-level partial R-indicators for economic activity in STS Manufacturing survey for January.



¹ NACE 152 = Visverwerking, NACE 158 = Vervaardiging overige Voedingsmiddelen, NACE 155 = Vervaardiging van zuivelproducten, NACE 171 = Bewerken en spinnen van textielvezels, NACE 174 = Vervaardiging van textielwaren, NACE 281 = Vervaardiging van metalen constructiewerken, ramen, deuren en kozijnen, NACE 283 = Vervaardiging van stoomketels, NACE 292 = Vervaardiging van overige machines en apparaten voor algemeen gebruik, NACE 294 = Vervaardiging van gereedschapswerktuigen, NACE 333 = Vervaardiging van apparaten voor de bewaking van industriële processen, NACE 342 = Carrosseriebouw en vervaardiging van aanhangwagens en opleggers and NACE 351 = Scheepsbouw en -reparatie

Figure 4.3.2: Unconditional (blue) and conditional (pink) category-level partial R-indicators for economic activity in STS Manufacturing survey for June.

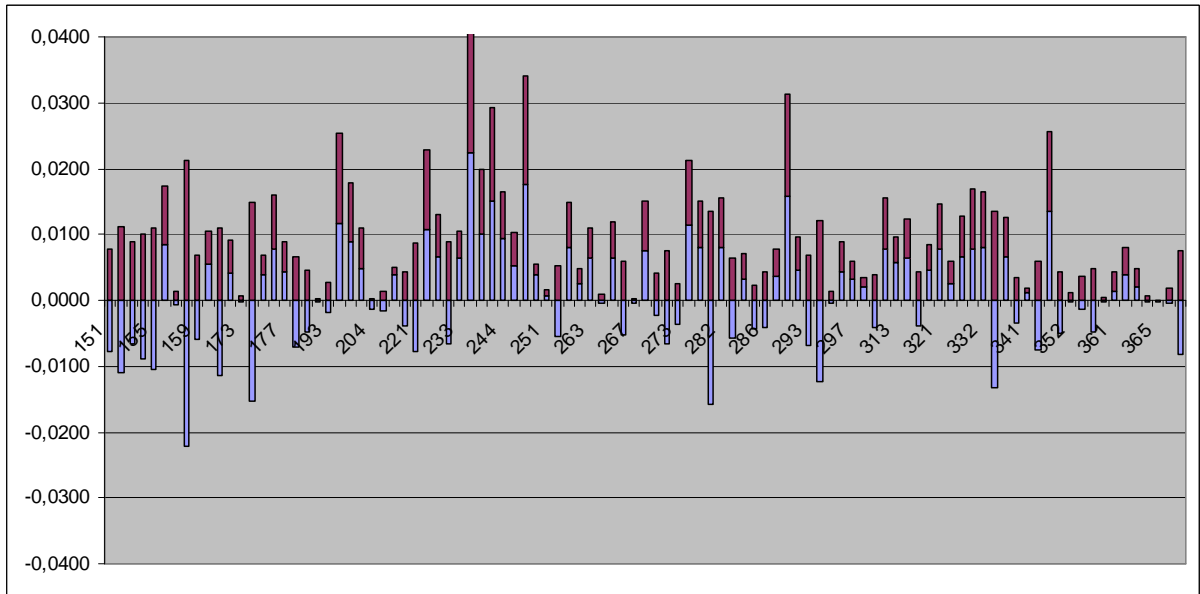


Figure 4.3.3: Unconditional (blue) and conditional (pink) category-level partial R-indicators for economic activity in STS Manufacturing survey for July.

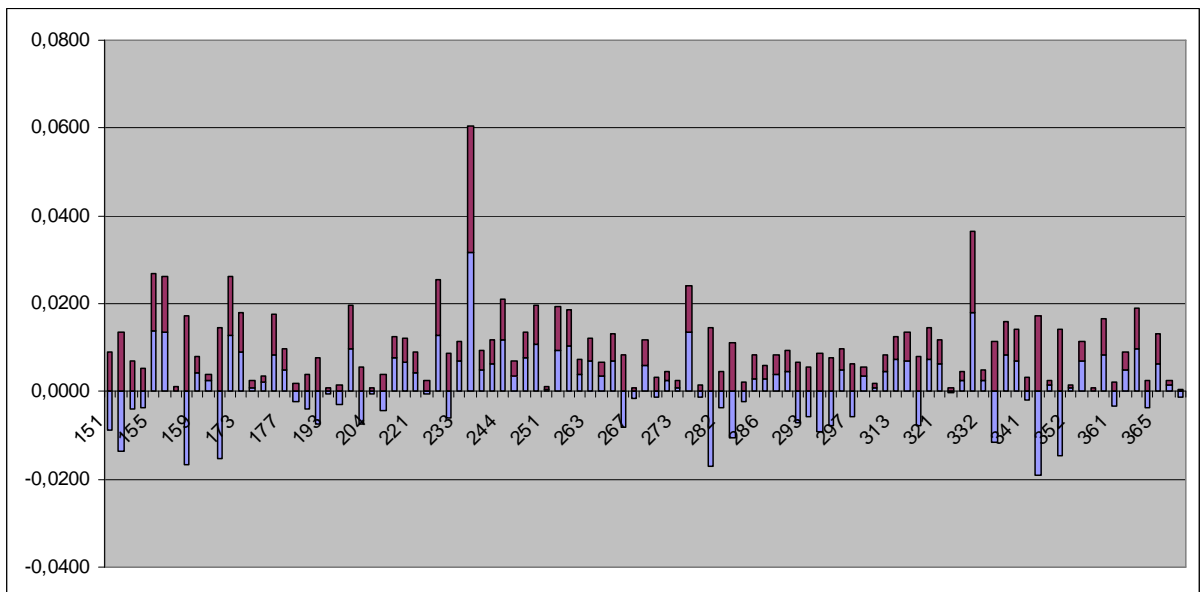
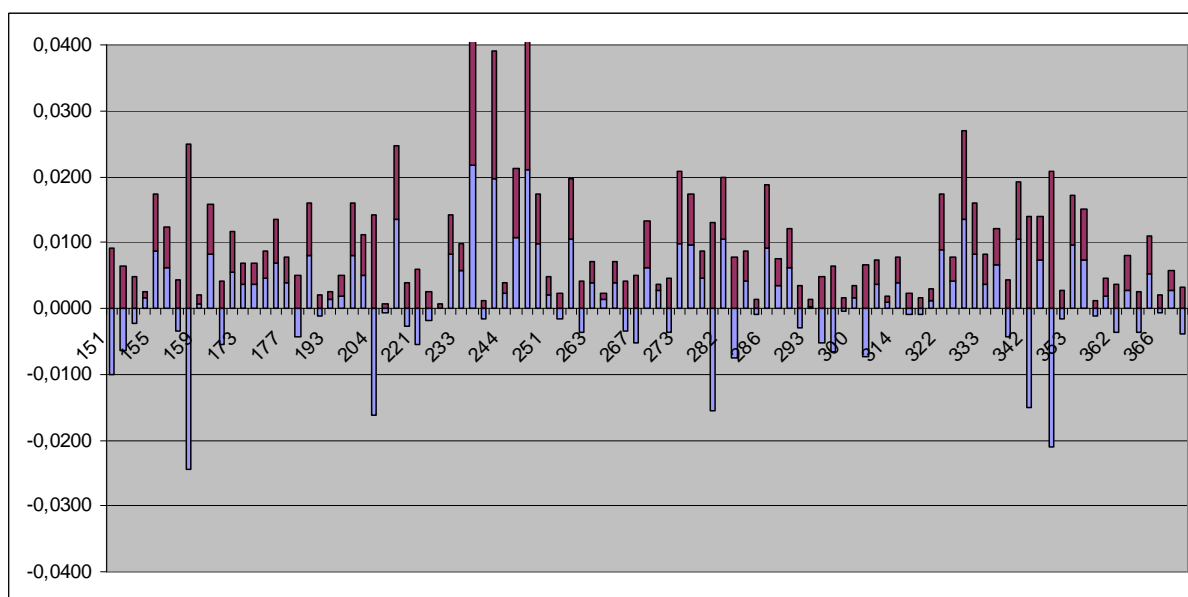


Figure 4.3.4: Unconditional (blue) and conditional (pink) category-level partial R-indicators for economic activity in STS Manufacturing survey for December.



We return to the main question of this subsection. Does economic activity play a role in obtaining a representative response? The partial R-indicators show that economic activity does play a role in the STS Manufacturing survey. The impact shows no seasonal influence, however, nor does the number of data collection days affect representativity. We find similar patterns for January, June, July and December and partial indicators are relatively stable during data collection.

Subsequently, a small number of economic activities are identified that impact the representativeness of response. Since we have only investigated 2007 data, it cannot be concluded that these types of business are persistently slow in responding and reporting.

For the STS Retail trade survey and VAT-response the type of business plays a less distinct role and representativity is dominated by reported VAT in previous year. For this reason, we did not investigate the impact of economic activity. However, we recommend a more in-depth analysis of the impact of reported VAT using partial R-indicators.

5. Conclusions

This paper compares the response rate and representativity of the STS survey and VAT data over months and during data collection. Both STS survey and VAT data can be used to produce monthly Short Term Business statistics. If possible, Statistics Netherlands wants to replace part of its survey efforts by data from administrative registers. For this, the available data should of course lead to accurate statistics.

In the comparison we focus completely on nonresponse error and ignore measurement error and sampling error. Clearly, the STS survey response has a bigger sampling error than the VAT data as the Tax Board records are a full enumeration of enterprises in the Netherlands. Measurement errors are conjectured to play an important role as well. However, there is little empirical evidence in favour of survey or administrative data. A complete comparison of both data sources should also account for these errors.

Since both types of data are subject to different kinds of missing data, i.e. nonresponse, and their datasets are filled in different ways, we compared the representativity of both data sets. The survey response rate increases gradually through time and is still far from 100% after a month of data collection. The VAT register also fills gradually in time because smaller enterprises report on a quarterly or annual basis. The representativity of VAT is lower than that of the survey, but since different models were used they can not be compared directly. However, the representativity of survey data is consistently high, while that of VAT data actually often declines as more data comes in. Furthermore, the VAT data shows considerable variation over months. January and July only have monthly reporters and typically score the lowest value for the R-indicators. The same can therefore be expected for February, April, May, August, October and November.

The lower representativity of the VAT data in some months implies that for these months nonresponse adjustment methods play a more dominant role than in others. As a consequence, comparability over months is hampered.

When replacing survey data with VAT data, also the inconsistency in the representativity of VAT data through the data collection process must be considered. We should decide on when statistics should be produced. When producing them as early as possible (at 25 days after the reporting period has ended) VAT is often most representative. When waiting longer (at 30 days), more data is available, but remarkably, the representativity may decrease for some periods.

We found that type of industry can impact the representativity of response given that the business size and reported turnover in the previous year are known. This was especially the case for the STS Manufacturing survey, where enterprises with certain economic activities show deviant response behaviour from other types of economic activity. For VAT, on the other hand, this effect was less pronounced. Therefore, at the publication level, the lack of impact of economic activity is an argument in favour of VAT data.

Although absolute response is higher for VAT data, in the future changing tax regulations may lead to underrepresentation of certain enterprise groups. Whether VAT can replace STS survey thus depends on more than just representativity of the current data.

One way to increase representativity is to focus on the way enterprises are approached and report their turnover, e.g. the survey mode, regular mail or electronic submission, and the reminder strategy. Future research should focus on the impact on representativity of mode and reminder strategy (for surveys). For VAT

data, these can not be controlled, so research should focus on using the available data in the best possible way. In this paper we investigated the unconditional and conditional impact of economic activity but largely ignored the impact of business size and previous year's turnover. Research into the role of data collection design features like survey mode, should also address the impact of these variables in order to optimize representativity.

References

- Van Delden, A., Aelen, F.W.L. (2008). Redesigning the chain of economic statistics at Statistics Netherlands: STS statistics as an example. IAOS conference 'Reshaping Official Statistics', 14-16 October 2008, Shanghai
- Hoekstra, M. (2007), Analyse op mode-effecten bij bedrijfsenquêtes (In Dutch), Afstudeerscriptie, BOO-2007-H003, Fontys Hogescholen, Tilburg.
- Nooij, G. de (2008), Representativity of Short Term Statistics, Afstudeerscriptie, Vrije Universiteit, Amsterdam.
- Schouten, B., Bethlehem, J. (2009), Representativeness indicators for measuring and enhancing the composition of survey response, Deliverable of 7th EU Research Framework Programme project RISQ, www.risq-project.eu.
- Schouten, B., Cobben, F., Bethlehem, J. (2009), Indicators for the representativeness of survey response, Survey Methodology, 35 (1), 101 – 113.
- Schouten, B., Luiten, A., Loosveldt, G., Beullens, K., Kleven, Ø. (2010), Monitoring and changing data collection through R-indicators and partial R-indicators, Deliverable of 7th EU Research Framework Programme project RISQ, www.risq-project.eu.
- Shlomo, N., Schouten, B., Skinner, C. (2010), Partial indicators for representative response, Working paper, University of Southampton, UK.
- Slootbeek, M., Van Bommel, K. (2010), Onderzoek naar overstappers/blijvers (In Dutch), internal CBS report.
- Vlag, P., Bergen, D. van den (2010), The use of VAT for short term statistics: some quality aspects, Statistics Netherlands, Proceedings ESSnet seminar on administrative data – Rome, March 18-19, 2010.

Appendix 1

RR2 for Manufacturing

Figure A1.1: RR2, based on VAT data for Manufacturing (Model 1), for January, June, July and December 2007.

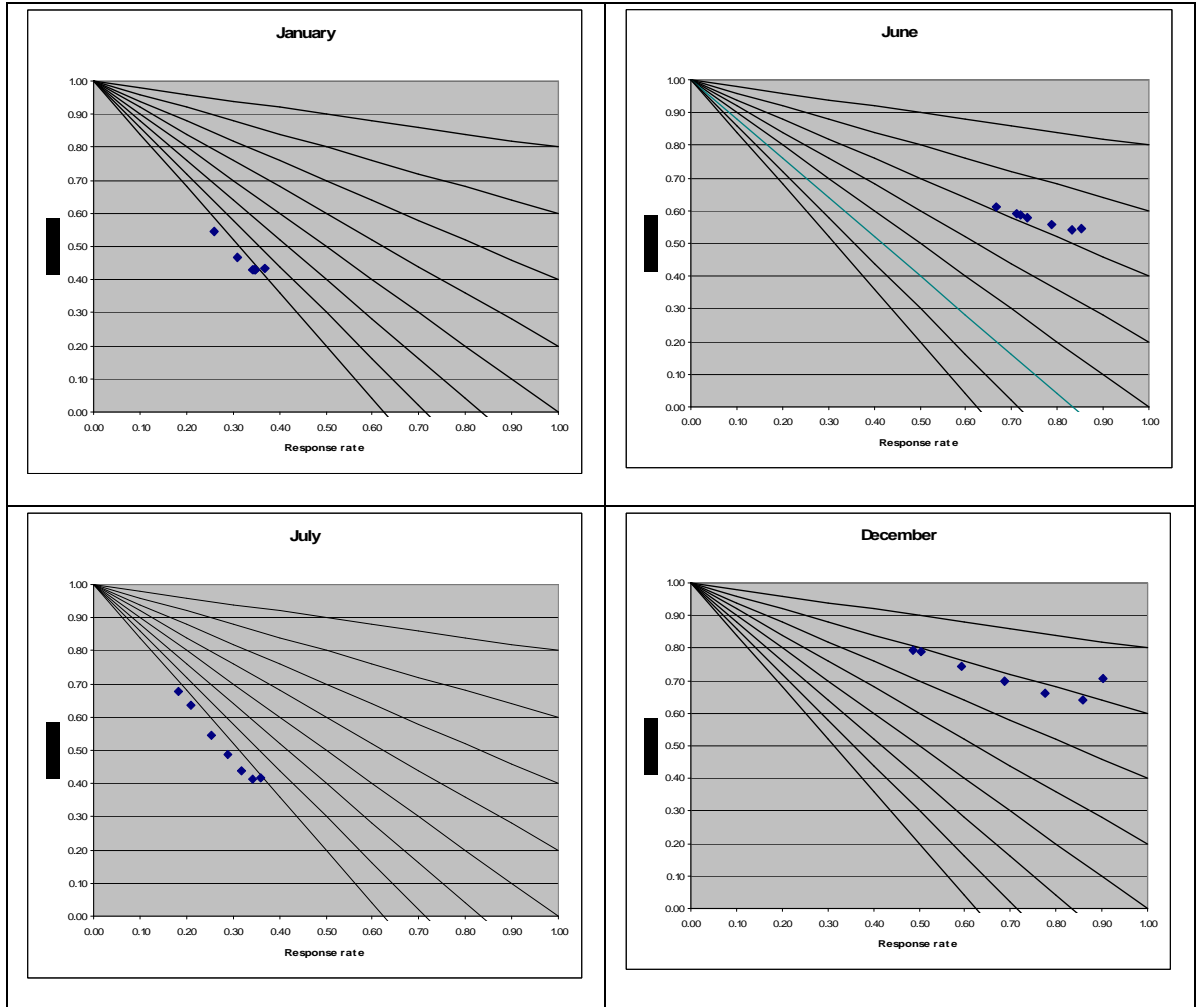
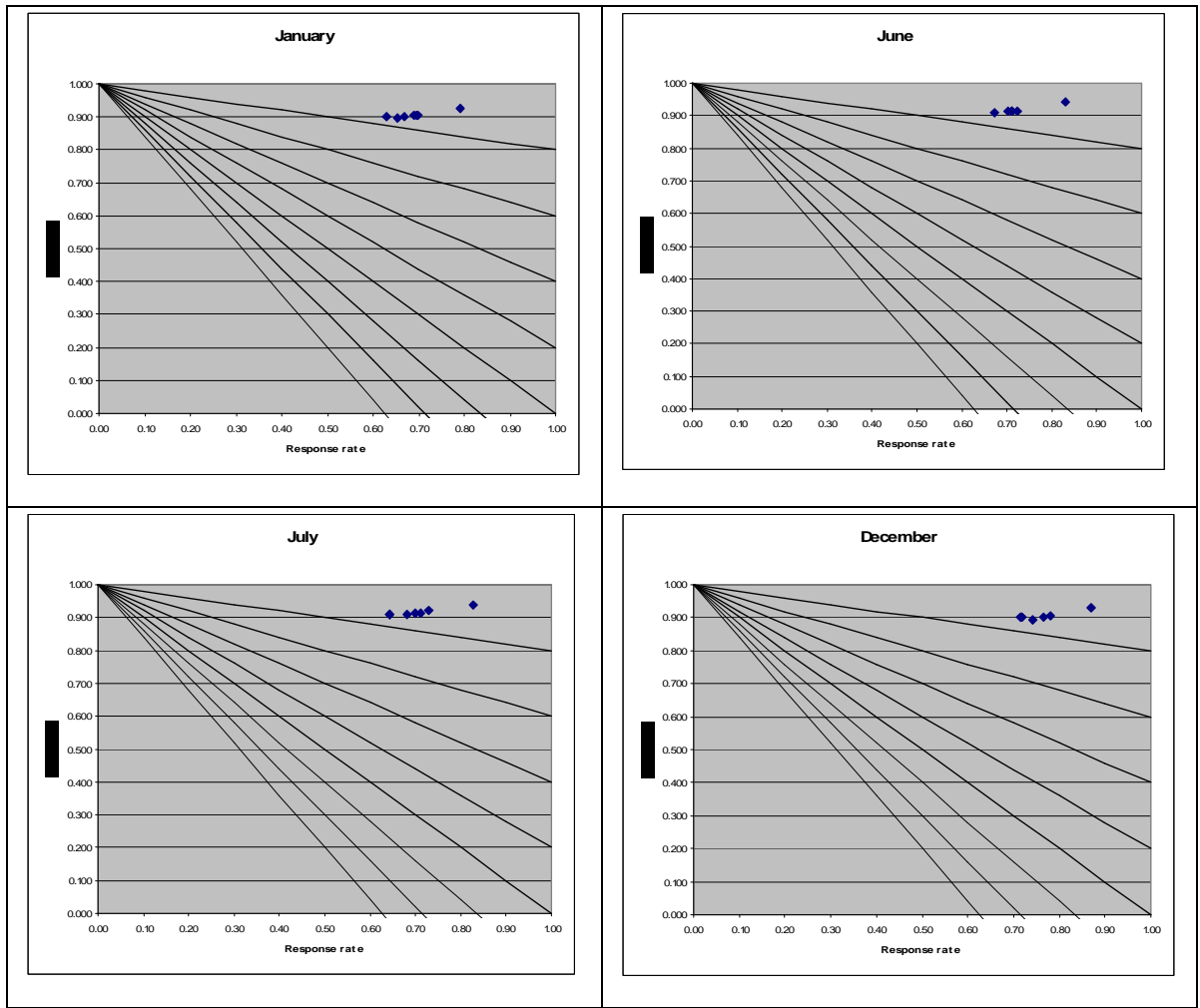
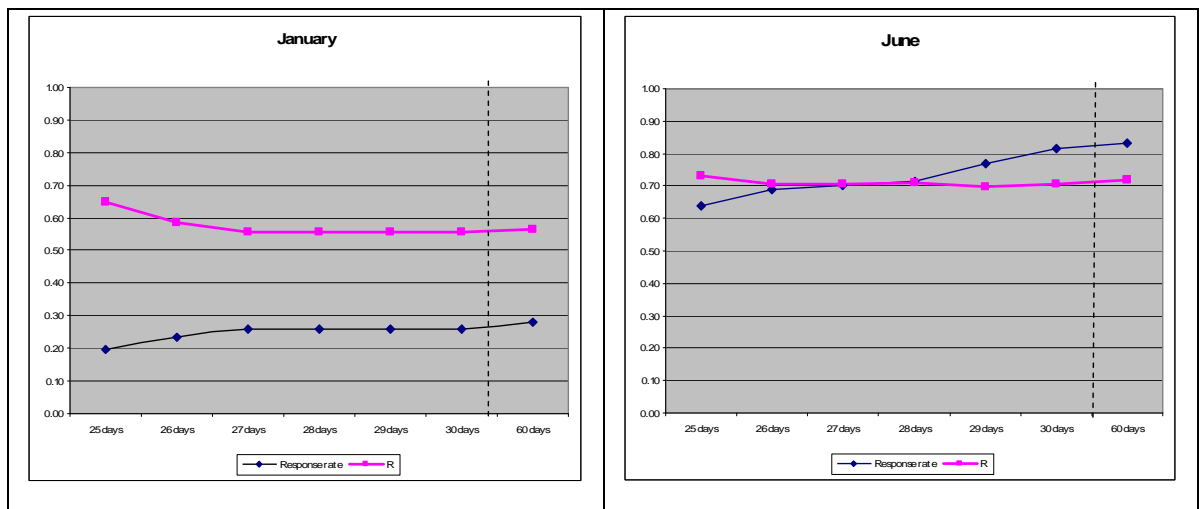


Figure A1.2: RR2, based on survey data for Manufacturing (Model 3), for January, June, July and December 2007.



Representativity and RR 2 for Retail trade – Model 2

Figure A1.3: Response rate and R-indicator based on VAT data for Retail trade (Model 2), for January, June, July and December 2007.



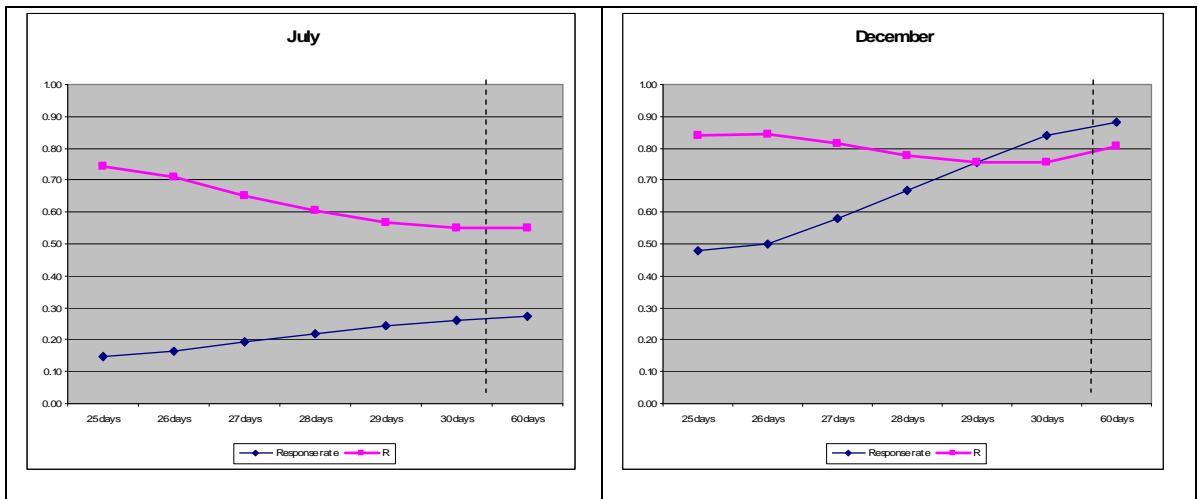
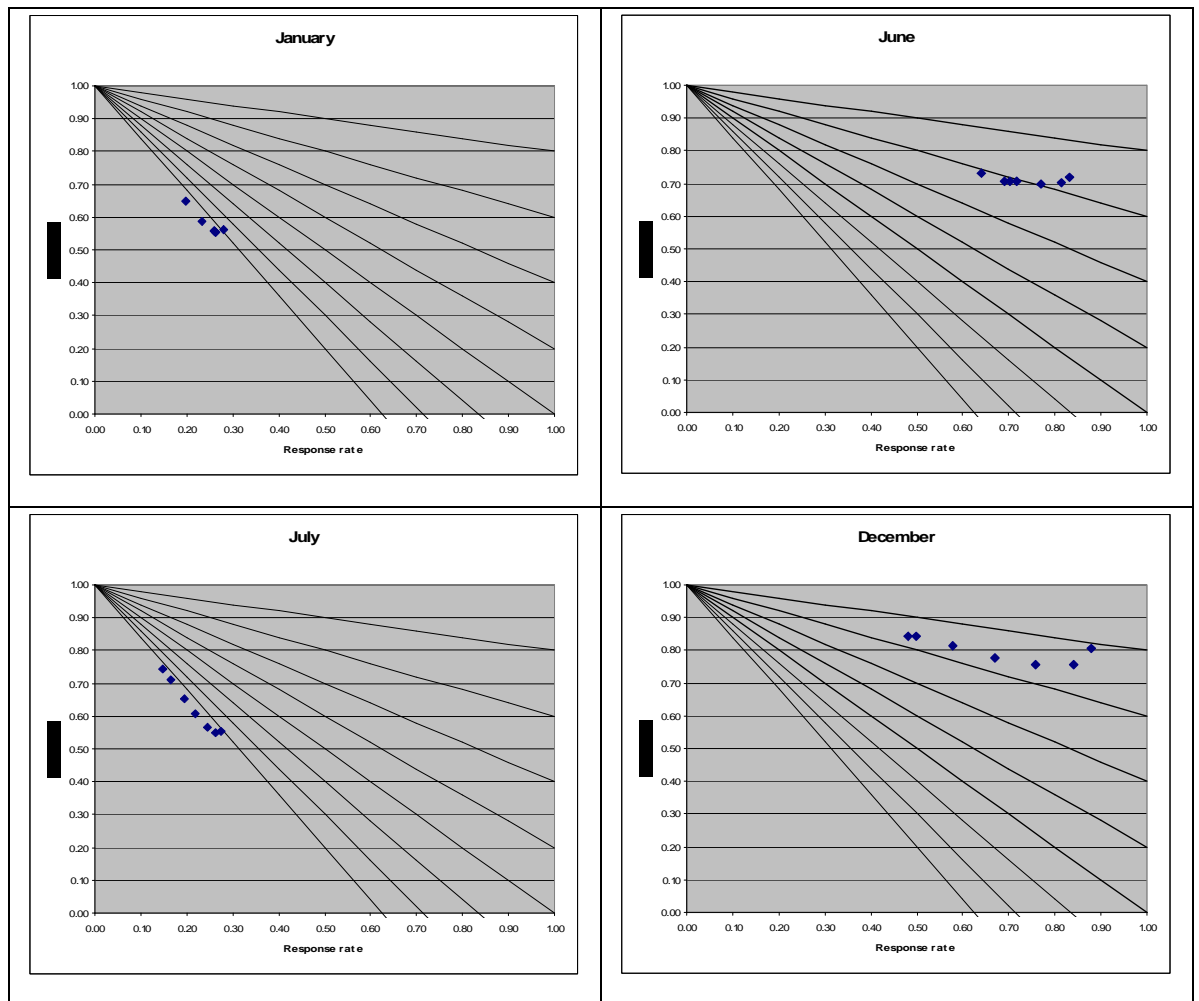


Figure A1.4: RR2, based on VAT data for Retail trade (Model 2), for January, June, July and December 2007.



Representativity and RR 2 for Manufacturing – Model 4

Figure A1.5: Response rate and R-indicator based on survey data for Manufacturing (Model 4), for January, June, July and December 2007.

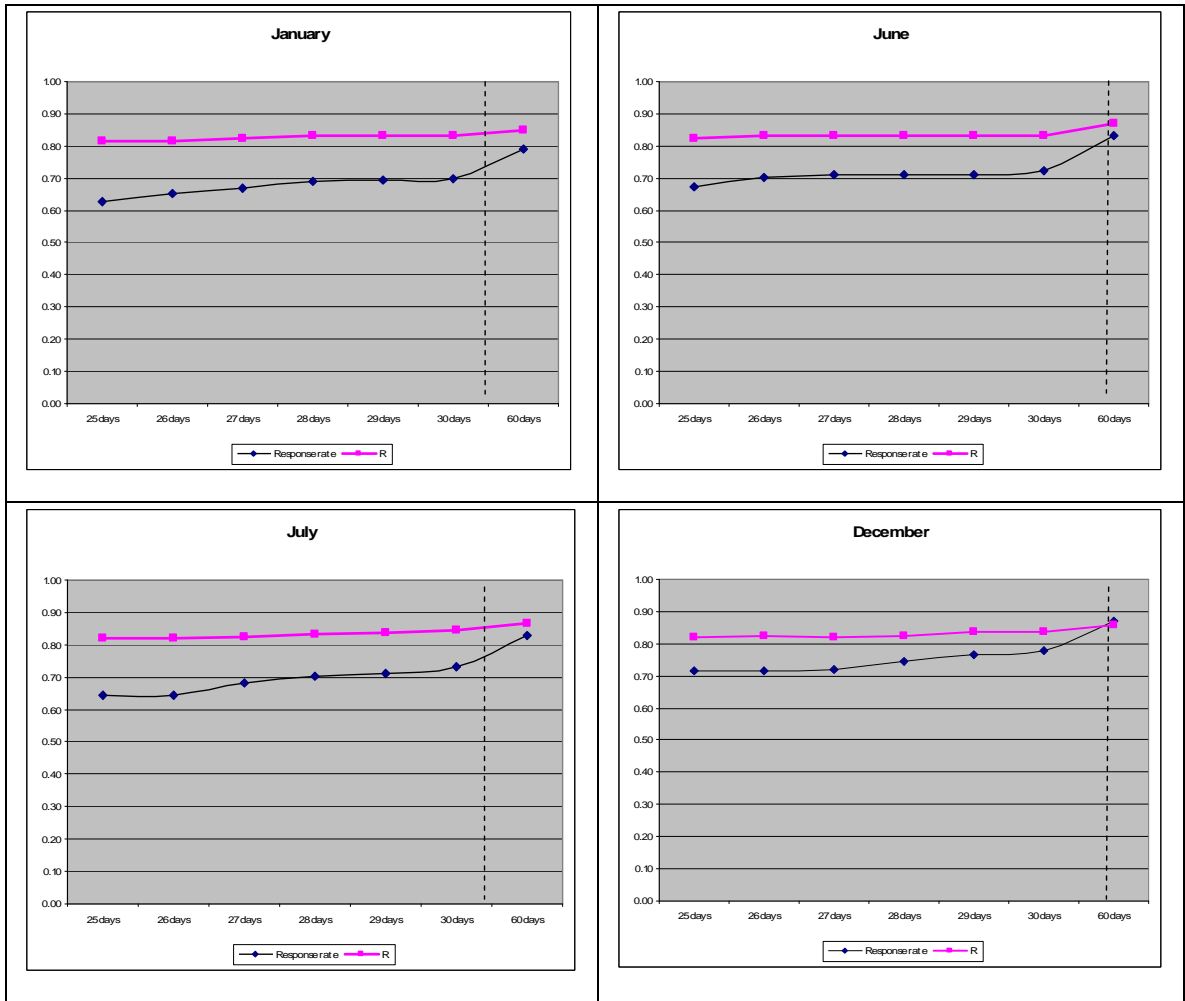
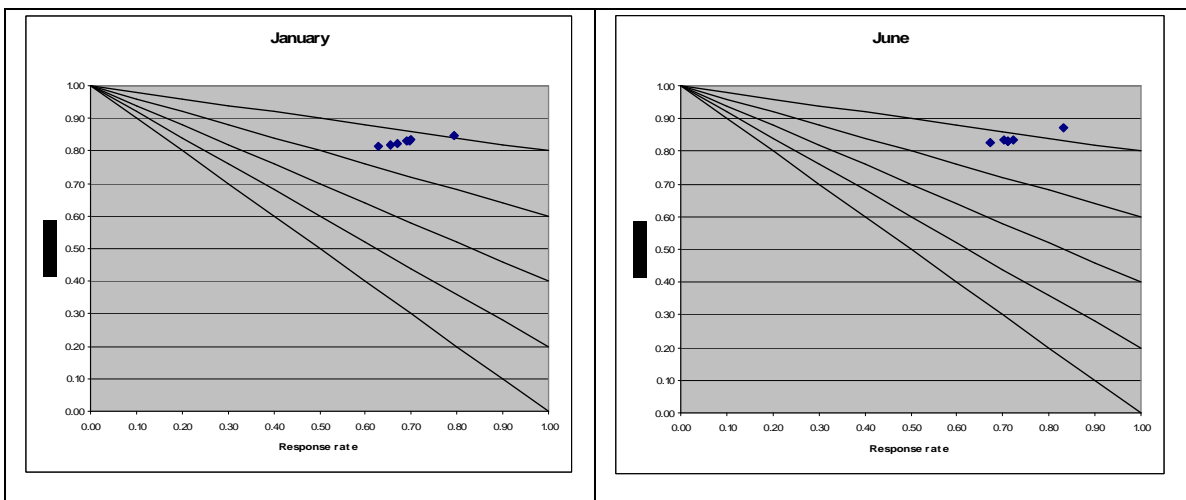
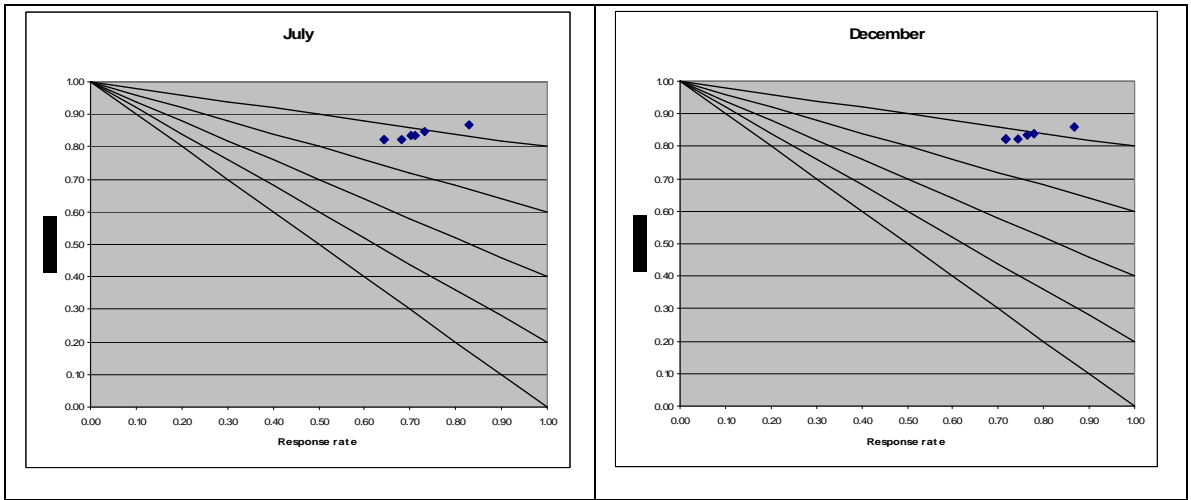


Figure A1.6: RR2, based on survey data for Manufacturing (Model 4), for January, June, July and December 2007.





Appendix 2

Table A2.1: Categories per variables

VAT(t-12)	Wages(t)
< € 2500	≤ € 0
€ 2501- € 10000	€ 0- € 2500
€ 10001- € 20000	€ 2501- € 10000
€ 20001- € 30000	€ 10001- € 20000
€ 30001- € 50000	€ 20001- € 30000
€ 50001- € 100000	€ 30001- € 50000
€ 100000- € 200000	€ 50001- € 100000
> € 200000	> € 100000
No data available*	No data available
	No Walvis-income

* VAT not reported or tax unit did not exist yet