A comparison on the company level of Manufacturing Business Sentiment Survey data and Realized Turnover

Discussion paper 05007

Statistics Netherlands

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C.H. Nieuwstad

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Statistics Netherlands

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Explanation of symbols

.	= data not available
*	= 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
2004–2005	= 2004 to 2005 inclusive
2004/2005	= average of 2004 up to and including 2005
2004/’05	= crop year, financial year, school year etc. beginning in 2004 and ending in 2005

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

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COMPARISON ON COMPANY LEVEL OF MANUFACTURING BUSINESS SENTIMENT SURVEY DATA AND TURNOVER

Using a classification method developed in this paper, the quality of qualitative survey data of the manufacturing industry at micro-economic level is investigated. For single companies, recent opinions on recent production developments are compared to quantitative results of industrial turnover. The results show that 57.6% of the analyzed companies give useful qualitative answers for calculating meaningful balance statistics such as producers' confidence. The level of agreement between quantitative and qualitative data for companies with seasonal patterns in turnover on average is 10.6%-points higher than for companies without seasonal patterns.

Keywords: Survey data, Quality, Qualitative data, Single company performance, Seasonal correction, Manufacturing industry turnover

1. Introduction

Business sentiment surveys are often used to provide estimators for current macroeconomic variables and likely movements in the economy. Many surveys only offer a qualitative indication of the recent past and expected near future. Data provided often only give the percentage of firms who respond an "up", "unchanged" or "down". Much research has been done on extracting quantitative indicators for the current and future state of the economy from this qualitative information. Three examples of this type of research are the probability method of Carlson and Parkin (1975), the regression method of Pesaran (1984) and an alternative approach by Mitchell et al. (2001 and 2002). This last approach is different, because it relates individual firms' categorical responses to official data, in contrast to the two former methods, that only use "aggregate responses" to quantify the survey data.

The implicit assumption of this type of use of business sentiment surveys is that at the early moment of responding to these surveys, firms actually have enough information to provide a correct indication of the development of production and/or turnover. The question thus rises, to which extent firms' early responses to survey data relate to later quantitative data on a single company basis. Do results from for example the Manufacturing Business Sentiment Survey (MBS) give good indications for microeconomic realisations, such as turnover and production developments of individual companies?

An important aspect that should not be neglected investigating these indications is the influence of seasonal patterns. This can be illustrated using an example. Assume that an ice-cream manufacturer in the Netherlands participates in the MBS. There are big chances that July is a warmer month than June. Therefore, there is a large possibility that there is an increase in production in July because with higher temperatures, generally more ice-cream is sold. The manufacturer knows this beforehand, and it is relatively easy to correctly answer a qualitative question of the MBS regarding the direction of production developments. Every year this situation is the same. Thus, seasonal patterns matter because they increase the agreement between the MBS and turnover, i.e. they influence the 'predictive power' of the MBS.

In this paper, the quality of the MBS is examined by linking and comparing on company level MBS and industrial turnover data. A distinction is made between companies with and without seasonal patterns in turnover. This makes it possible to gauge the amount of influence of seasonality on the results.

The paper is organised as follows. In chapter 2 the linking process of the survey data with turnover is described. In chapter 3 a classification is developed with categories describing the degree to which surveys provide answers that are in accordance to turnover developments. Next, in chapter 4 and chapter 5 results for applying this classification for two questions of the MBS using not seasonally adjusted turnover are presented. In chapter 6 details and results of the procedure used to adjust turnover of individual companies for trading day and seasonal effects are described.[1] The influence of seasonal patterns in turnover on results of the classification of single companies is discussed in chapter 7. Finally, conclusions and some final remarks are given in chapter 8.

[1] Only turnover data has been corrected for seasonal effects, because the trichotomic nature of the answer categories of question 1 of the MBS makes a seasonal correction (very) difficult.

2. Data used

In this chapter, the data set used is presented. First, in section 2.1 information on the data sources for turnover and MBS are given and the linking process is described. Next, in section 2.2 differences in survey process and timeliness are discussed.

2.1 Data sources and coupling process

For the results of this paper two sources of data were used. The first source is the MBS database, which contains data of individual companies. Each company is classified into a NACE 4-digit level and a size class (5-9)[2]. Data available in the system at the 17th of March 2004 have been used for the calculations made in this paper. This corresponds to the months 200101 up to and including 200312. The second source is the statistic on Industrial Turnover. Two sources are available: an 'old' database, which contains figures from 199301 up to and including 200303, and a 'new' database, with figures from 200304 and later.

The MBS provides answers of individual companies, characterized by a WEID code, to (among others) the following two questions. Question 1 is "Last month's production level (not taking the influence of holidays into account) has…", with answer categories "increased" (1), "remained the same" (2) and "decreased" (3). And question 2 is "The average production level over the next three months (not taking the influence of holidays into account) will…" "increase" (1), "remain the same" (2) and "decrease". The statistic on Industrial Turnover provides turnover data of individual companies, characterized by a BEID code. For each value of turnover, there is an additional variable available, which indicates if this value has been estimated or not, e.g. to cope with non-response. At company level, 10% of the turnover values have been estimated.

Using a linking scheme from WEID to BEID for the Business Survey data it is possible to link this data to the turnover data. However, for the business survey period of 200101 until 200311, 9 BEIDS (out of 1861) have more than 1 WEID in at least one period. The WEID/BEID relation is not necessarily one-to-one. This problem was overcome by just leaving these 9 BEIDs out of the linking process. Additionally, for 59 BEIDs of the MBS there is no turnover information available. The result is that for 1793 BEIDS there is at least 1 value for turnover available in the period of 199901 up to and including 200311.

For 1000 BEIDs corrections for seasonal patterns of turnover have been made. For these adjustments, turnover data for the period 199301 up to and including 200311 have been used.

[2] Companies with 20 to 50, 50 to 100, 100 to 200, 200 to 500 and more than 500 employees, are classified as size class 5, 6, 7, 8, 9, respectively.

2.2 Difference in survey process and timeliness

For first publication industrial turnover is surveyed between t+0 and t+28 (approximately) after the end of the period under review, with approximately 65% response (weighted, average over many years) for the first estimate (Van der Stegen, 2004). At t=60, and t=90 the response is approximately 83% and 88%, respectively.

For MBS data, first, it is important to note that the way the MBS questionnaire is surveyed is different compared with the method mainly used for other statistics. A 'time shift of one month' is introduced. Define the coming month containing the days *t..t+28/30/31* as month *M*. Now, what is called the '*questionnaire of month M*' is sent out to the participating companies at around t-*1*. Answers are collected between t+0 and t+24. The (not weighted) response to the questionnaire is approximately 90% for the final estimate. To illustrate with more detail the difference in terminology between the surveying of the MBS and turnover, an example is provided in Figure 1.

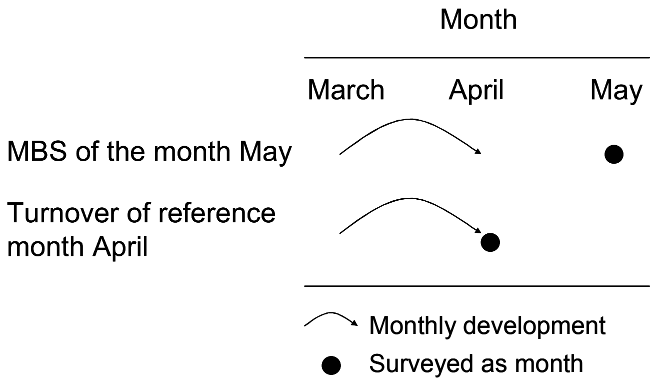

Figure 1. Example of the difference in surveying terminology for question 1 of the MBS and turnover data.

In this figure the three months March, April and May are considered. For the MBS the answers to the question 'Last month's production level (not taking the influence of holidays into account) has…' for the 'questionnaire of the month May' are by definition labelled as May and *also stored in the MBS database under the month May.* But, according to the phrasing of the question, the respondents for the 'questionnaire of the month May' give answers regarding the development of the production level of *April compared to March.* This fact has to be kept in mind during the whole remainder of this paper. As said earlier, a time shift of one month is introduced.

For the turnover statistic, turnover of '*reference period*' April is surveyed in May, *but stored at April* in the turnover database. Thus, the monthly turnover development of April can be calculated straightforward by relating the turnover value of April to the turnover value of March. No time shift is introduced.

The final conclusion is that *effectively*, the qualitative result of production development of April compared to March of the MBS is usually published around two weeks earlier than the results of the turnover development of April compared with March. However, for a theoretical successful comparison, values of question 1 of the MBS for a certain month have to be compared to turnover developments of one month earlier.

3. Classification of individual companies

In this chapter, a start is made to analyse the relation between MBS and turnover data. A classification system for individual companies is developed. First, in section 3.1 an assumption for the time shift between MBS and turnover data is discussed. After this, in section 3.2 cases for companies with "logically ordered" answer categories are presented. In section 3.3 cases of companies without "logically ordered" answer categories are given. The total classification consists of 31 groups. This is too much to do analysis and interpret results. Therefore, in section 3.4, the number of groups is reduced by merging. An optimal number of data points needed to classify a company in a certain category is determined in section 3.5. Finally, in section 3.6 the number of classification categories is reduced further to a more practical classification inspired by the producers' confidence indicator.

3.1 Time shift of question 1 of the MBS in relation to turnover data

In order to be able to compare question 1 of the MBS to turnover data[3] it is necessary to have information on the relation between these two statistics (see also section 2.2). It is important to know to which month of the turnover data the MBS relates the best. The easiest way to obtain this information is to look at the way how question 1 of the MBS has been put into words: "Last month's production level (not taking the influence of holidays into account) has…". In this formulation, clearly the term 'last month's' is used. Thus, to make a start with the research, it is logical to assume that the persons who answer to the MBS give answers that correspond to the phrasing of the question, i.e. to 'last month'. Thus that, for example, the MBS of May relates best to the monthly turnover development of April. The appropriateness of this time shift is validated in section 4.4.

3.2 Companies with "logically ordered" answer categories

In this section the relationship between turnover and the three response categories of question 1 is analysed at company level. To make a comparison between business survey data and turnover, for each company the absolute monthly development, $amdT_{BEID,t}$, of turnover, T, is calculated:

$$amdT_{BEID,t} = T_{BEID,t} - T_{BEID,t-1}$$

According to the assumption made in section 3.1, it seems logical to examine if for each company the answers to question 1 are consistent with the absolute monthly

[3] Strictly speaking, question 1 of the MBS should be compared with production data. However, production data are generally not available at company level. For this reason, turnover is used as a proxy for production. Doing this, it is assumed that monthly inventory changes and price developments are relatively small. The proxy may also be less accurate in branches of industry where instalments take place.

developments of turnover of one month earlier, $amdT_{BEID,t-1}$. This means, that if category 1 ("increased"), 2 ("remained the same") or 3 ("decreased") is answered, $amdT_{BEID,t-1}$ is larger than zero, zero (or in some interval around zero) or smaller than zero, respectively. For analysis, an average $amdT_{BEID,t-1}$ value is calculated for each response category 1, 2 and 3. For each time t a company answers "increased" (1) to question 1 of the MBS, all values of $amdT_{BEID,t-1}$ belonging to these "increased"'s are averaged to $\overline{amdT1}_{BEID}$. The same is done for response categories 2 and 3, resulting in $\overline{amdT2}_{BEID}$ and $\overline{amdT3}_{BEID}$, respectively.

A logical relationship between $\overline{amdT1}_{BEID}$, $\overline{amdT2}_{BEID}$ and $\overline{amdT3}_{BEID}$ can be expected. Suppose that a more optimistic answer to question 1 corresponds to a higher value of $amdT_{BEID,t-1}$. Then it can be expected that $\overline{amdT1}_{BEID} > \overline{amdT2}_{BEID}$, because $\overline{amdT1}_{BEID}$ consists of averages of $amdT_{BEID,t-1}$ for which the company answered "increased" in the MBS and $amdT_{BEID,t-1}$ of averages of $amdT_{BEID,t-1}$ for which the company answered "remained the same". Following this reasoning, it would also be logical that $\overline{amdT2}_{BEID} > \overline{amdT3}_{BEID}$. This situation is given in Figure 2.

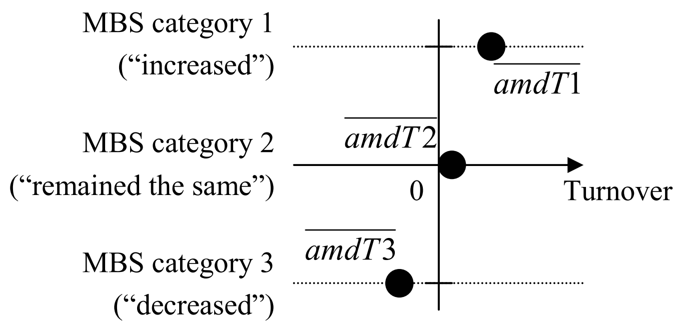

Figure 2. ($\overline{amdT1} > \overline{amdT2}$), ($\overline{amdT2} > \overline{amdT3}$), $\overline{amdT1}$ >0 and $\overline{amdT3}$ <0, label of this case: 123_FS123_NOBIASMBS.

But there remains a question to be solved: does question 1 of a company have a bias or not?

The result for question 1 for a company can be defined positively biased if $\overline{amdT1}_{BEID}$ <0, see Figure 3 as an example.

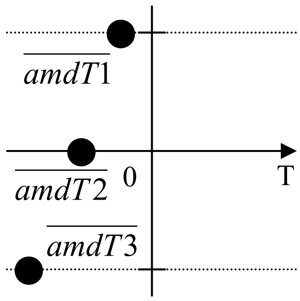

Figure 3. Label of this case: 123_FS123_POSBIASMBS.

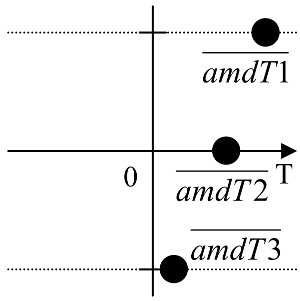

Figure 4. Label of this case: 123_FS123_NEGBIASMBS.

In this case, the answer to question 1 is too optimistic compared to the proxy for the realisation.

Similarly, it is possible to define a negative bias when $\overline{amdT3}_{BEID}$>0. An example is Figure 4. Finally, a possible definition for no bias is $\overline{amdT1}$>0 and $\overline{amdT3}$<0, see Figure 2. For further reference in this paper, these three cases have been given a label.

Fifteen other, more obscure cases for which $\overline{amdT1}_{BEID}$, $\overline{amdT2}_{BEID}$ and $\overline{amdT3}_{BEID}$ have a "logical relationship" have been defined. To not flood this paper with images, they are, including their label, given in Appendix A.

3.3 Companies without "logically ordered" answer categories

In section 3.2 examples for "logically ordered" answer categories are given. In this section, a classification for not "logically ordered answer categories" will be given. A company without "logically ordered" answer categories is defined as a company where a more optimistic answer to question 1 corresponds to a lower value of $amdT_{BEID,t-1}$. Then it can be expected that $\overline{amdT1}_{BEID}$ <= $\overline{amdT2}_{BEID}$ and $\overline{amdT2}_{BEID}$ <= $\overline{amdT3}_{BEID}$. An unbiased version of this case is given in Figure 5.

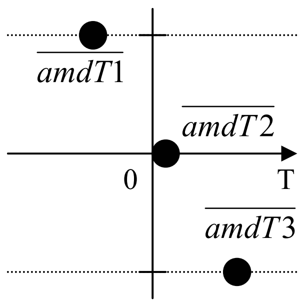

Figure 5. 'Reversed version' of Figure 2. In this case ($\overline{amdT1} <= \overline{amdT2}$), ($\overline{amdT2} <= \overline{amdT3}$), $\overline{amdT1}$ <0 and $\overline{amdT3}$ >0.

This case is called the 'reversed version' of Figure 2, because in the criterion ($\overline{amdT1} > \overline{amdT2}$) and ($\overline{amdT2} > \overline{amdT3}$) only the 'greater than test' has been changed by an unchanged or smaller test.

For 13 of the 18 cases defined in Appendix A it is possible to define a “reversed version”. These 13 cases are classified in one single group, called “other companies without logically ordered answers”.

The classification presented in this and the former section is exhaustive: if it is applied, all companies in the data set are either classified as a company with “logically ordered answer categories” or as a company with not “logically ordered answer categories”.

3.4 Simplification of the classification

The classification developed in 3.2 and 3.3 consists of 19 groups. To simplify further analysis, the number of groups is reduced to 7 by combining them into categories. The results for these categories are given in Table 1.

Table 1. Combined classification.

Type	Category
123_FS123_NOBIASMBS	1
13_FS13_NOBIASMBS	1
1_NOBIASMBS	1
3_NOBIASMBS	1
123_FS13_NOBIASMBS	2
123_FS123_POSBIASMBS	3
123_FS123_NEGBIASMBS	3
12_O1>O2_POSBIASMBS	3
23_O3<O2_NEGBIASMBS	3
13_FS13_POSBIASMBS	3
13_FS13_NEGBIASMBS	3
1_POSBIASMBS	3
3_NEGBIASMBS	3
2_QSTBIASMBS	4
12_O1>O2_QSTBIASMBS	5
23_O3<O2_QSTBIASMBS	5
123_FS13_POSBIASMBS	6
123_FS13_NEGBIASMBS	6
“Other companies without logically ordered answers”	7

Category 1 is a group for which companies give unbiased logically ordered answers. For category 2, the answers to question 1 are unbiased and logically ordered with respect to the answer categories “increased” and “decreased”, but “remained the same” is not ordered logically. Category 3 is a group of companies for which the response is biased, but logically ordered. Category 4 is the group of companies which always answer “remained the same” to question 1 the MBS, with unknown bias. Category 5 is a group where companies give logical ordered answers, but the bias is not known. Category 6 contains all companies with biased and “logically ordered answers” with respect to the answer categories “increased” and “decreased”, but the “remained the same” category is not ordered logically. Category 7 is the last category, containing all companies without “logically ordered answers”.

3.5 Number of points per company needed for classification

3.5.1 Total data set

To begin with, in this section the classification presented in 3.4 will be applied to all companies in the data set. However, there is still an issue to be solved. In 3.2 averaging was introduced to calculate $\overline{amdT1}_{BEID}$, $\overline{amdT2}_{BEID}$ and $\overline{amdT3}_{BEID}$. The question remains how many data points have to be used to calculate these averages.

Regarding the classification process, two aspects are important. The first is to be able to obtain reasonable stable classifications of single companies (aspect 1). The second is to be able to calculate frequency distributions of the number of companies classified in a certain category (aspect 2). If the number of data points (N) used to classify a single company is too low, it is difficult to obtain a stable single company classification. But if the amount of available data is limited, and the number of data points used for single company classification is high, too little companies are classified to obtain meaningful frequency distributions for each classification category.

For the data set studied, the second aspect is certainly of importance. To show this, the distribution of the number of companies that provide a certain number of data points available to determine it's classification is given in Figure 6.

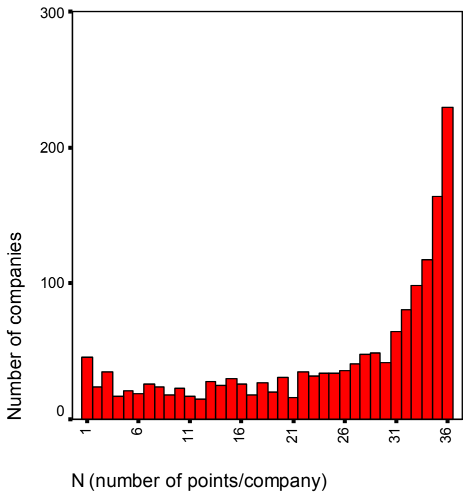

Figure 6. Number of companies for each number of data points available to calculate $\overline{amdT1}_{BEID}$, $\overline{amdT2}_{BEID}$ and $\overline{amdT3}_{BEID}$.

First, it is noted that this distribution is not surprising. The peak of 229 companies for N=36 corresponds to companies that have been permanently in sample. N's smaller than 36 are observed because companies are introduced and removed from the sample of the MBS, and thus are not permanentely available in the data set. From these 'dynamics' it follows, that it is not possible to use at the same time many points for classification on a company level and to calculate stable frequency distributions for different categories. For example, if a minimum of 10 data points would be used for company classification, 1380 companies would be classified and could be used for the calculation of frequency distributions of the different categories. However, if 36 points would be used for single company classification, only 229 companies could be used to calculate these distributions. This reasoning implies that there is a quality trade-off between the classification of single companies and frequency distributions of categories.

This trade-off could be investigated in detail, but for the remainder of this paper the minimum number of data points needed to calculate a reasonable stable classification of companies is determined by an empirical method. The classification of each company is calculated consecutively using companies with N=1..36, N=2-36, N=3-36, … , N=35-36 and finally N=36. After this, the percentage of companies in each category is calculated. The results of these calculations are given in Figure 7.

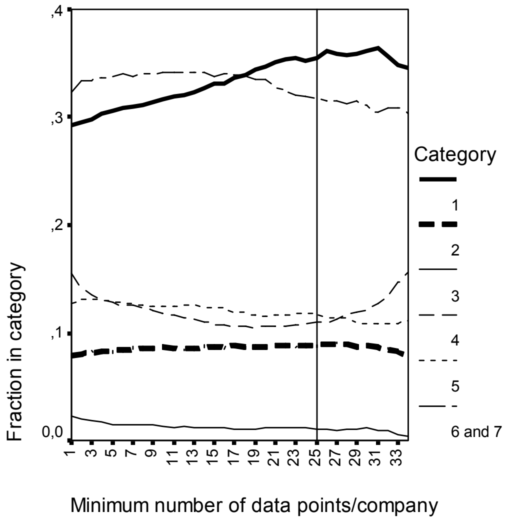

Figure 7. Percentage of companies in each category as a function of the number of data points (N) used for classifying each company.

Define the percentage of companies in category i as C_i. First the development of C_1 as a function of N is considered. From N=1 to N=25 C_1 has a rising trend. After the minimum of N=25 it is approximately constant until 31 data points. Then there is a small decrease.

The initial rise can be explained by the idea that it is not possible to 'stable' classify a single company using too little data points (aspect 1). When N=25-31 (1003-753 companies) the classification is stable, because C_1 is approximately constant between N=25 and N=31. For N>=32 the number of companies used to calculate the percentage of companies in category 1 is reduced to 688 or less. This may be too little to calculate a stable number of companies in category 1 (aspect 2), explaining why C_1 is smaller than when N=25.

C_2, C_3 and C_5 do not show large variations when N is varied. C_4 is close to its minimum value for N=25 and C_{6+7} is slightly decreasing when N increases.

From the above reasoning, and 'tuning' C_1 empirically to its 'optimum' it is decided to use at least 25 points to classify a company into one of the seven defined categories.

3.5.2 Breakdown by size class

An extra test for the result derived in 3.5.1 is to split the data into different groups and to look if the results are similar. The results for the percentage of companies in category 1 as a function of N for size class 5-9 are given in Figure 8.

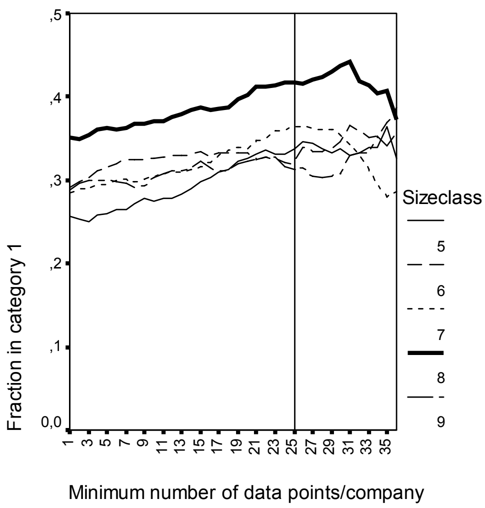

Figure 8. Percentage of companies classified in category 1 as a function of the number of data points (N) used for classifying each company.

The results are similar compared to the results of 3.5.1. For all size classes for N=1 to N=25 C_1 has a rising trend. Around N=25 (N=25±4, say) C_1 for each size class is fairly stable. Above N=29, the results of C_1 for each size class tend to get more volatile, indicating that the number of companies classified into category 1 gets too little to get stable results.

An interesting point is that C_1 for size class 8 is in general larger than C_1 for the other four size classes. This result will be examined further in section 4.2.

3.6 Classification groups inspired by Dutch producers' confidence

Another, more practical way to construct classification groups is to classify companies into groups with respect to their potential use for an indicator that exists in practice. This indicator could be the producers' confidence (PC), which is calculated using balances of answers of companies to questions of the MBS. Calculating balances implies only using the answers "increased" and "decreased" of the questions of the MBS. Now, assume that the PC should follow the movements of turnover (the proxy used in this paper for production) as well as possible. In this case companies classified into categories for which the "increase" and "decrease" answer categories are "logically ordered" and unbiased with respect to turnover should be used for calculating the PC. From this point of view, category 1 can always be used, because it has “logically ordered answer categories” without bias. This category is labelled group A. Category 3 could be used for the PC if the bias of the answers of companies can be corrected[4]. The combination of categories 1 and 3 is labelled group B. Categories 2 and 6 have “logically ordered answer categories” with respect to the answer categories “increased” and “decreased”, but the “remained the same” category is not ordered logically. Companies in category 2 do not have a bias; companies of category 6 could be used for the producers’ confidence if the bias of the answers could be corrected. Finally, the combination of categories 1, 2, 3 and 6 is labelled group C. As a summary, the definition of the three groups is given in Table 2.

Table 2. Groups inspired by the producers’ confidence.

Category	Group
1	A
1+3	B
1+2+3+6	C

[4] This is a bias correction on single company level. For the Dutch producers’ confidence, an adjustment is made for bias at the aggregate level of total manufacturing industry.

4. Analysis of results of classifying companies using question 1

In this chapter results of classifying companies using question 1 of the MBS are presented. First, results for the classification of all companies without a breakdown to size class or NACE 2-digit level is given in section 4.1. Next, results with breakdowns into size class and NACE 2-digit level are given in sections 4.2 and 4.3, respectively. Finally, in section 4.4, the assumption made on the size of the time shift between question 1 of the MBS and turnover data (see section 3.1) is checked.

4.1 Total

To get a first impression of the distribution of the different companies over the different classification types which have been defined in section 3.2 and 3.3, the results of applying the classification to question 1 of the data set are given in Table 3.

Table 3. Results of applying the classification to question 1.

Type	Percentage	Category
123_FS123_NOBIASMBS	35.5	1
13_FS13_NOBIASMBS	-	1
1_NOBIASMBS	-	1
3_NOBIASMBS	-	1
123_FS13_NOBIASMBS	8.9	2
123_FS123_POSBIASMBS	0.4	3
123_FS123_NEGBIASMBS	0.5	3
12_O1>O2_POSBIASMBS	0.2	3
23_O3<O2_NEGBIASMBS	-	3
13_FS13_POSBIASMBS	-	3
13_FS13_NEGBIASMBS	-	3
1_POSBIASMBS	-	3
3_NEGBIASMBS	-	3
2_QSTBIASMBS	11.0	4
12_O1>O2_QSTBIASMBS	4.5	5
23_O3<O2_QSTBIASMBS	7.3	5
123_FS13_POSBIASMBS	5.6	6
123_FS13_NEGBIASMBS	6.6	6
“Other companies without logically ordered answers”	19.6	7

Strikingly, there are eight classification types into which not a single company is classified. Thinking a bit further, this is not a very strange result. The minimum number of points used for classifying each company is 25 (see section 3.5). Over such a long period of time, most companies would respond at least one time to each of the three answer categories “increased”, “remained the same” or “decreased”. All classification types into which no companies are classified are types where there are less than three answer categories used for classifying the company.

Results based on 7 categories

The results presented in Table 3 are difficult to interpret, because the number of classification types is rather large. This is why, see also section 3.4, seven categories were defined. These categories are also given in Table 3. This makes it possible to calculate the results for these seven groups, which are presented in Table 4.

Table 4. Results for classifying companies on the basis of question 1.

	Category							Total
	1	2	3	4	5	6	7	
Count	356	89	11	110	118	122	197	1003
% of total	35.5%	8.9%	1.1%	11.0%	11.8%	12.2%	19.6%	100.0%

According to these results, 35.5% of the companies answer completely logical to question 1, because they are classified into category 1. This category contains companies which give “unbiased logically ordered answers” (see 3.4). Furthermore, 19.6% of the companies answer completely illogical to question 1, because they are in category 7, “Other companies without logically ordered answers”. Thus, in total more than half (55.1%) of all the companies is classified into categories 1 and 7.

Of all companies, 11.0% are classified into category 4. This seems a high percentage for a category which contains only companies which for a longer period of time only answer “remained the same” to question 1 the MBS, with unknown bias. Of course it is possible that monthly turnover changes for these companies in general are (very) small. In this case “remained the same”-answers to the MBS would relate well to turnover developments. However, if a company always answers “remained the same” and monthly turnover developments show reasonable fluctuation, the question rises, if the company is “lazy” in answering question 1 of the MBS and tries to finish the questionnaire fast or that the company does not have enough information to correctly predict turnover developments.

The remaining four categories (34.0% of all companies) are a bit more difficult to interpret. They can be biased (category 3 and 6), unbiased (category 2), have an unknown bias (category 5), have “logically ordered answer categories” (category 3 and 5), do not have “logically ordered answer categories” (category 2 and 6), or share a combination of these five characteristics.

Of all the companies, 8.9% is classified into category 2, companies with unbiased and “logically ordered answer categories” with respect to the answer categories “increased” and “decreased”, but “remained the same” is not ordered logically (see section 3.4). The average fraction of companies for which the response is biased, but which have “logically ordered answer categories” (category 3) is only 1.1%. Category 5 contains 11.8% of the companies. This is the group where companies have “logically ordered answer categories”, but the bias is not known. Finally, category 6 contains 12.2% of the companies. This category contains all companies with biased but “logically ordered answer categories” with respect to the answer categories “increased” and “decreased”, but the “remained the same” category is not ordered logically.

Results based on classification groups inspired by Dutch producers' confidence

It is also possible to use the three groups defined in section 3.6. The results for this classification are given in Table 5.

Table 5. Results for classifying companies on the basis of question 1.

	Group		
	A	B	C
Count	356	367	578
% of total	35.5%	36.6%	57.6%

35.5% of the companies are classified into group A (of course this is the same as the number of companies classified into category 1 of Table 4). Groups B and C contain 36.6% and 57.6% of the total number of companies, respectively. Thus, if a bias correction of question 1 of the MBS would be possible and only balances are calculated, almost 60% of the companies giving answers to question 1 supply useful information.

4.2 Breakdown by size class

So far, the results are only presented as averages for all companies. However, in section 3.5.2 it was already shown that making a breakdown using the size class of each company gives interesting results. Results of this breakdown, presented for the three groups based on the producers' confidence (see section 3.6), are given in Table 6. For more detailed results, based on seven categories, see Appendix B.

Table 6. Results for classifying companies on the basis of question 1. Breakdown using the size class of each company.

			Group		
			A	B	C
Size class	5	Count	65	69	101
		% within size class	33.9%	35.9%	52.6%
	6	Count	73	75	122
		% within size class	32.0%	32.9%	53.5%
	7	Count	93	95	154
		% within size class	36.5%	37.3%	60.4%
	8	Count	90	93	141
		% within size class	41.7%	43.1%	65.3%
	9	Count	35	35	60
		% within size class	31.3%	31.3%	53.6%
Total		Count	356	367	578
		% within size class	35.5%	36.6%	57.6%

With 41.7% (6.2%-point higher than the average value) size class 8 has the highest percentage of all size classes of companies classified in group A. For size class 7, the percentage of companies classified into category A is 36.5%, only 1.0%-point above average and the closest to the average of all size classes. Size classes 5, 6 and 9 all have values for the percentage of companies classified in group A below average, 1.6%-point, 3.5%-point and 4.2%-point, respectively.

Category B does not give much more information than category A, because the percentages of companies classified into category A and B do not differ much. The maximum difference is 2.0%-point for size class 5.

Size class 8 has, with 65.3%, also the highest percentage of companies classified into group C. A striking detail is that the percentage of companies classified into group C is higher for size class 6 than for size class 5, while for group B the percentage of size class 5 is higher than the percentage of size class 6.

These results do not support the view that smaller companies give "better" answers to question 1 of the MBS, e.g. because they have a more complete overview of the entire business. This idea has to be rejected, because classification percentages of size classes 5 and 6 are slightly lower than classification percentages op size classes 7 and 8.

The results presented in this section have to be interpreted with caution, because all percentages for different size classes are different, but relatively close to the percentage of the total without breakdown according to size classes. A first, general conclusion might be that apparently, for size classes 5 and higher, the size of the company does not practically contribute to its capacity to correctly assess the direction of turnover development at the time the MBS is held.

4.3 Breakdown by NACE 2-digit

In this section results of a breakdown by NACE 2-digit level of the classification of companies using question 1 is discussed. The breakdown in the three groups based on the producers' confidence is presented in Table 7. For more detailed results, based on seven categories, see Appendix B.

Table 7. Results for classifying companies on the basis of question 1. Breakdown using the NACE 2-digit level of each company.

NACE 2-digit	Description	Group A	Group B	Group C
15	Food products and beverages	41.1%	41.9%	65.3%
16	Tobacco products	16.7%	16.7%	33.3%
17	Textiles	23.8%	23.8%	57.1%
18	Wearing apparel	23.1%	23.1%	38.5%
19	Leather (and products)	33.3%	40.0%	46.7%
20	Wood (and products)	22.6%	25.8%	48.4%
21	Paper, paperboard (and products)	51.9%	51.9%	66.7%
22	Publishing, printing and reproduction	60.7%	60.7%	71.4%
23	Coke, refined petroleum and nuclear fuel	50.0%	50.0%	66.7%
24	Chemicals (and products)	44.0%	44.0%	62.0%
25	Rubber and plastic products	37.1%	37.1%	60.0%
26	Glass, earthenware, cement, lime and plaster articles	28.0%	29.3%	57.3%
27	Basic metals	38.1%	40.5%	57.1%
28	Fabricated metal products	36.9%	38.3%	58.4%
29	Machinery and equipment	29.5%	31.1%	48.4%
30	Office machinery and computers (*not active in NL*)	0.0%	0.0%	0.0%
31	Other electrical machinery and apparatus	22.2%	22.2%	55.6%
32	Radio, television and communication equipment and apparatus	14.3%	14.3%	28.6%
33	Medical, precision and optical instruments, watches and clocks	47.8%	47.8%	69.6%
34	Motor vehicles, trailers and semi-trailers	24.2%	24.2%	54.5%
35	Other transport equipment	17.2%	24.1%	41.4%
36	Furniture and other manufacturing n.e.c.	40.6%	40.6%	65.6%
15-36	Total	35.5%	36.6%	57.6%

Table 7 contains a lot of information. It is valuable for quality assessment of the MBS, because it gives for each NACE 2-digit an indication of the percentage of companies which give “correct” answers to the MBS. This gives the option to select NACE 2-digit groups where the number of companies with “correct” answers is relatively low, and try, if possible, to improve the quality of the response. The above table invites to a lot of discussions. However, enough data has to be available for a NACE 2-digit group in order to make these discussions meaningful. A threshold of 20 or more companies for each group is chosen. This means that NACE 2-digit groups 16, 18, 19, 23, 30 and 32 (indicated in grey) will be excluded from a discussion[5]. A couple of “highlights” of the results will be given below.

Companies belonging to NACE 2-digits 21 (Paper, paperboard (and products)), 22 (Publishing, printing and reproduction) and 33 (Medical, precision and optical instruments, watches and clocks) on average give the best answers to question 1 of the MBS. These NACE 2-digits have the highest percentages of companies classified into groups A, B and C. The percentages classified into groups A and B for these three NACE 2-digit levels are between 47.8% (NACE 33) and 60.7%

[5] NACE 2-digit groups 16, 18, 19, 23, 30 and 32 are not analysed separately in the whole remainder of this paper.

(NACE 22). For group C, the percentages lie between 66.7% (NACE 21) and 71.4% (NACE 22).

Companies belonging to NACE 35 (Other transport equipment), 31 (Other electrical machinery and apparatus) and 20 (Wood (and products)) on average give less good answers to question 1 of the MBS. Percentages of companies classified to group A are respectively 17.2%, 22.2% and 22.6%; to group B 24.1%, 22.2% and 25.8%; to group C 41.4%, 55.6% and 48.4%.

The above results can be seen as a quality assessment of the MBS: NACE 2-digits 21, 22 and 33 have are performing better than NACE 2-digits 35, 31 and 20. Of course all this is conditional on the assumption that using turnover as a proxy for production does not give a too large deviation from reality.

4.4 Verification of the time shift of question 1 in relation to turnover data

In this section a check is made to verify that the time shift between question 1 of the MBS in relation with turnover in practice is one month (see also section 3.1). The approach is as follows. The percentage of companies classified into category 1 is also calculated using $amdT_{BEID,t-3}$, $amdT_{BEID,t-2}$ and $amdT_{BEID,t}$ instead of $amdT_{BEID,t-1}$. If the percentage of companies classified into category 1 for one of these additional three cases is larger than for $amdT_{BEID,t-1}$, the time shift seems different than assumed. The results of these calculations, made on the on the NACE 2-digit level, are given in Table 8.

Table 8. Validation of time shift for question 1 of the MBS on the NACE 2-digit level. NACE 2-digit levels indicated in light grey are excluded from analysis (see also section 4.3). The most interesting values of the percentage of companies classified into category 1 are indicated with dark grey. Due to the time shifting, the total number of companies classified for each time shift varies between 982 and 1003.

NACE 2-digit	Percentage of companies classified into category 1 using			
	$amdT_{BEID,t-3}$	$amdT_{BEID,t-2}$	$amdT_{BEID,t-1}$	$amdT_{BEID,t}$
15	16.1	18.5	41.1	12.9
16	0.0	16.7	16.7	0.0
17	14.3	23.8	23.8	9.5
18	7.7	38.5	23.1	23.1
19	6.7	0.0	33.3	6.7
20	16.1	9.7	22.6	12.9
21	16.7	13.0	51.9	3.7
22	7.1	42.9	60.7	17.9
23	16.7	0.0	50.0	16.7
24	13.0	10.0	44.0	11.0
25	17.1	25.7	37.1	14.3
26	11.0	30.5	28.0	9.8
27	11.9	14.3	38.1	9.5
28	12.1	14.8	36.9	8.1
29	17.2	10.7	29.5	13.1
30	0.0	0.0	0.0	0.0
31	7.4	14.8	22.2	11.1
32	0.0	14.3	14.3	14.3
33	17.4	8.7	47.8	8.7
34	15.2	12.1	24.2	21.2
35	3.4	10.3	17.2	10.3
36	12.5	12.5	40.6	15.6

For 14 of the 16 analysed NACE-2-digit groups the maximum percentage of companies classified into category 1 is obtained using $amdT_{BEID,t-1}$. This indicates that on average for these groups, the persons who answer question 1 of the MBS really interpret 'last month' as one month earlier.

NACE 26 shows slightly different behaviour. Using $amdT_{BEID,t-2}$, the percentage of companies classified into category 1 is 30.5%, just 2.5% more than when $amdT_{BEID,t-1}$ is. For NACE 26, comparing MBS data with turnover data of two months earlier, instead of data of 'last month', would be slightly more appropriate. For NACE 17, of the companies 23.8% is classified into category 1 both for using values of $amdT_{BEID,t-1}$ and $amdT_{BEID,t-2}$. For this group, comparing with turnover data of 'last month' or of two months earlier does not seem to make any difference. Because the deviations for both NACE 17 and 26 with respect to the timing assumption made in section 3.1 are very small, always values of $amdT_{BEID,t-1}$ have been used when comparing to question 1 of the MBS. This was mainly done to keep uniformity in the analysis process.

5. Comparison between classifying using question 1 and question 2

Until now, turnover was related to the assessment of firms of "recent production" (question 1). In this chapter, question 2 on "production expectations" will also be included. In section 5.1 a view on the interpretation of question 2 of the MBS is given. Next, results of classifying companies using question 1 and question 2 are presented. A comparison without breakdown into size class or NACE 2-digit level is given in section 5.2. Results with breakdowns into size class and NACE 2-digit level are given in sections 5.3 and 5.4. Only groups A and C of the classification based on the producers' confidence are compared. Extensive results in 7 categories with breakdowns into size class and NACE 2-digit are given in Appendix B and C. Finally, in section 5.5 a check is made if the time shift between turnover data and MBS results for question 2 is as can be expected.

5.1 Interpretation of question 2 of the MBS

Until now, only question 1 of the MBS was studied. In the remaining part of this paper, also question 2 of the MBS, "The average production level over the next three months (not taking the influence of holidays into account) will…", is considered. The way this question will be interpreted is changed slightly compared to the interpretation suggested by the phrasing of this question. This is done because it seems unlikely that the entrepreneurs who fill in the questionnaire are able to predict turnover (benchmark for production) three months ahead in order to be capable to evaluate the expression $mean(T_{BEID,t} + T_{BEID,t+1} + T_{BEID,t+2}) - T_{BEID,t-1}$, the mathematical representation of the variable asked to evaluate in the questionnaire.

In this paper, it is assumed that for question 2 the respondents in practice give answers regarding the present month, and therefore $amdT_{BEID,t}$ is used as comparison variable for question 2. It is difficult to assess whether the assumption is entirely correct or not. A very detailed investigation of the correctness of this assumption will not be discussed in this paper. Comparison tables for breakdowns into size class and NACE 2-digit level for the two different views are given in Appendix D. In general, the differences between the two methods are small[6]. The results may even be dependent on size class and/or NACE 2-digit level. To determine how the results of question 2 *exactly* have to be interpreted in practice remains a topic for future research.

[6]To give a quick idea: using $amdT_{BEID,t}$, for total industry, 26.6% is classified into category 1. Using $mean(T_{BEID,t} + T_{BEID,t+1} + T_{BEID,t+2}) - T_{BEID,t-1}$ this percentage is 27.5%, resulting in a small difference of -0.9%.

5.2 Total

Results for comparing results of classifying companies using question 1 and question 2 are given in Figure 9.

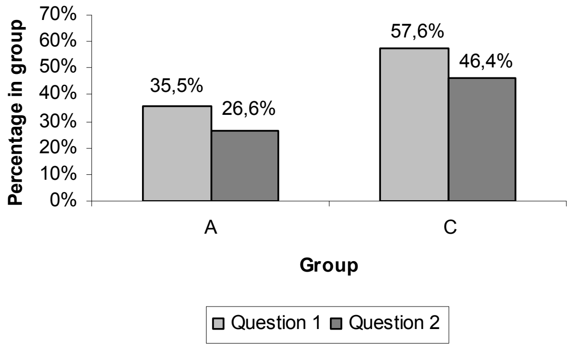

Figure 9. Comparison of classification groups A and B for question 1 and question 2.

It is obvious that it is in general more difficult to predict the future than to assess the past. For question 1, 8.9% more companies classify to group A than for question 2. For group C, this difference is 11.2%-point.

5.3 Breakdown by size class

A breakdown of the results of section 5.2 using the size class of each company is given for group A in Figure 10 and for group C in Figure 11.

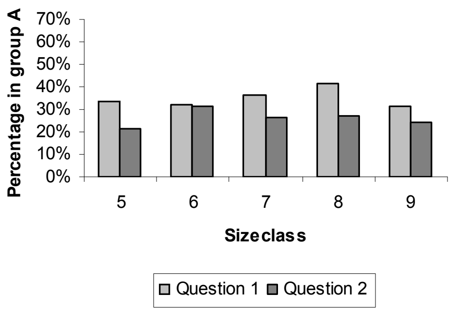

Figure 10. Comparison of the percentage of companies in group A for question 1 and question 2. Breakdown by size class.

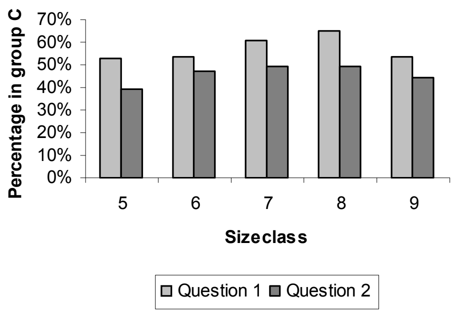

Figure 11. Comparison of the percentage of companies in group C for question 1 and question 2. Breakdown by size class.

For companies of every size class it seems more difficult to predict the future than to assess the past. However, for size class 6 the number of companies classified into group A using respectively question 1 and question 2 is, with a difference of 0.5%-point almost the same (for other size classes, this difference is at least 6.9%-point). Thus, if only results for group A are considered, for companies belonging to size class 6 prediction seems almost as easy as assessing the past.

When only group A is considered, size class 6 seems the best predicting class. However, just as in section 4.2 for question 1, the results for question 2 for different size classes have to be interpreted with caution, because all percentages for different size classes are different, but relatively close to the percentage of the total without breakdown.

If group C is considered, the results would not be much different. However, for interpretation, group A may be preferable, because this group only contains “logically ordered answer categories” without bias, whereas group C also includes answers to the MBS that are not totally “logical”.

5.4 Breakdown by NACE 2-digit

A breakdown of the results of section 5.2 using the NACE 2-digit level of each company is given for group A in Figure 12 and for group C in Figure 13.

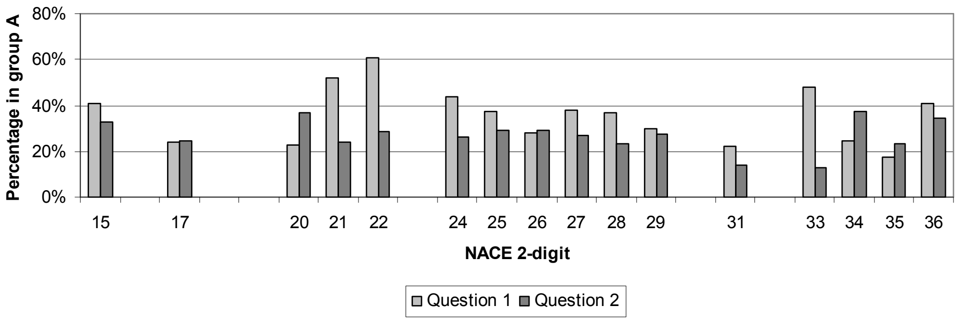

Figure 12. Comparison of the percentage of companies in group A for question 1 and question 2. Breakdown by NACE 2-digit.

First, results for classification into group A are considered. For the companies of most NACE 2-digit levels, predicting is more difficult than assessing the past. However, for NACE 17 (Textiles), 20 (Wood (and products)), 26 (Glass, earthenware, cement, lime and plaster articles), 34 (Motor vehicles, trailers and semi-trailers) and 35 (Other transport equipment), predicting seems more easy. However, these results have to be interpreted with caution. For NACE 35, for example, turnover might not be a good proxy for production, because lots of instalments take place in this branch of the manufacturing industry. This could give erroneous results.

Also striking is that companies of NACE 21 (Paper, paperboard (and products)), 22 (Publishing, printing and reproduction) and 33 (Medical, precision and optical instruments, watches and clocks) are relatively good at assessing the past, but poor at predicting the future. If the companies’ amount of production for next month is difficult to forecast, this might be a reason why answers to question 2 are less accurate.

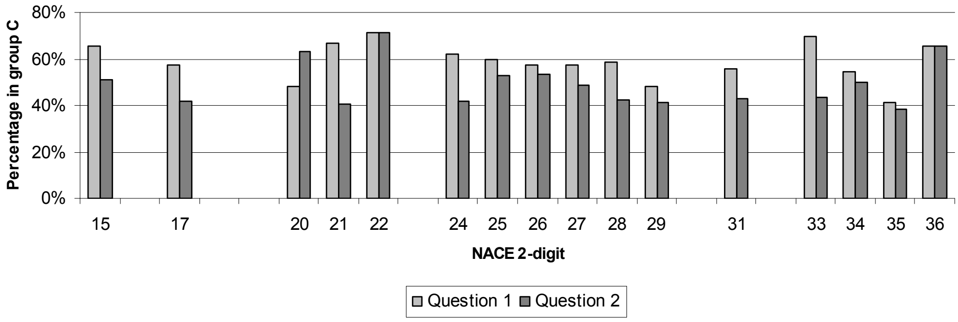

Figure 13. Comparison of the percentage of companies in group C for question 1 and question 2. Breakdown by NACE 2-digit.

If group C is considered, only NACE 20 has a higher percentage of companies classified into this group for question 2 than for question 1. Further, results for group C show similar patterns as the results for group A.

5.5 Verifying of the time shift of question 2 in relation to turnover data

In this section, the assumption made in section 5.1 that there is no time shift between question 2 and turnover developments is checked. The approach taken is the same as for question 1 described in section 4.4. The percentage of companies classified into category 1 is also calculated using $amdT_{BEID,t-2}$, $amdT_{BEID,t-1}$, $amdT_{BEID,t+1}$, $amdT_{BEID,t+2}$, $amdT_{BEID,t+3}$ and $amdT_{BEID,t+4}$ instead of $amdT_{BEID,t}$. If the percentage of companies classified into category 1 for one of these additional six cases is larger than for $amdT_{BEID,t}$, the time shift seems different than assumed. The results of these calculations, made on the NACE 2-digit level, are given in Table 9.

Table 9. Validation of time shift for question 2 of the MBS on the NACE 2-digit level. NACE 2-digit levels indicated in light grey are excluded from analysis (see also section 4.3). The most interesting values of the percentage of companies classified into category 1 are indicated with dark grey. Due to the time shifting, the total number of companies classified for each time shift varies between 856 and 999.

NACE 2-digit	Percentage of companies classified into category 1 using						
	$amdT_{BEID,t-2}$	$amdT_{BEID,t-1}$	$amdT_{BEID,t}$	$amdT_{BEID,t+1}$	$amdT_{BEID,t+2}$	$amdT_{BEID,t+3}$	$amdT_{BEID,t+4}$
15	15.6	13.9	32.8	16.4	12.3	5.7	9.8
16	0.0	0.0	0.0	0.0	0.0	0.0	0.0
17	17.1	12.2	24.4	9.8	9.8	7.3	7.3
18	14.3	14.3	0.0	0.0	14.3	7.1	0.0
19	14.3	7.1	14.3	14.3	0.0	0.0	14.3
20	10.0	0.0	36.7	16.7	23.3	10.0	13.3
21	13.0	22.2	24.1	9.3	13.0	14.8	16.7
22	7.1	14.3	28.6	21.4	10.7	17.9	3.6
23	0.0	0.0	50.0	33.3	0.0	0.0	0.0
24	15.3	12.2	26.5	15.3	11.2	10.2	15.3
25	5.9	23.5	29.4	26.5	11.8	8.8	8.8
26	3.8	16.5	29.1	21.5	7.6	11.4	11.4
27	7.3	12.2	26.8	17.1	12.2	7.3	12.2
28	13.1	16.6	23.4	20.0	10.3	15.2	9.7
29	8.5	12.8	27.4	16.2	12.0	11.1	12.0
30	0.0	0.0	0.0	0.0	0.0	0.0	0.0
31	14.3	17.9	14.3	10.7	0.0	10.7	10.7
32	0.0	0.0	25.0	25.0	25.0	0.0	12.5
33	17.4	17.4	13.0	17.4	13.0	26.1	4.3
34	12.5	12.5	37.5	18.8	6.3	9.4	0.0
35	19.2	3.8	23.1	3.8	0.0	11.5	23.1
36	15.6	15.6	34.4	28.1	34.4	6.3	12.5

For 13 of the 16 analysed NACE-2-digit groups the maximum percentage of companies classified into category 1 is obtained using $amdT_{BEID,t}$. This indicates that on average for these groups, the persons who answer question 2 of the MBS in practice refer to the present month.

Two groups showing different behaviour are NACE 31 (Other electrical machinery and apparatus) and 33 (Medical, precision and optical instruments, watches and clocks). First it is noted that for these groups the percentages of companies classified into category 1 are relatively low, say below 20%, for most of the turnover time shifts. This might indicate that it is difficult to correctly classify the companies regardless of the time shift chosen, i.e. that there is no clear relationship between MBS and turnover data.

The most striking behaviour shows NACE 36 (Furniture and other manufacturing n.e.c.). The percentage of companies classified into category 1 is relatively high, say above 20%, when $amdT_{BEID,t}$, $amdT_{BEID,t+1}$ and $amdT_{BEID,t+2}$ are used to calculate the classification. This might indicate that the entrepreneurs of this branch are better capable to assess the long-term future than entrepreneurs of other branches.

6. Seasonal adjustment of turnover on the company level

In the remainder of this paper the influence of companies with and without seasonal patterns in turnover on results presented earlier will be examined separately. To do this, seasonality in single company turnover has to be analyzed. The procedure used for adjusting turnover of 1000 individual companies for trading day and seasonal effects is described in section 6.1. The criterion used to decide if turnover of a company has an identifiable seasonal pattern is discussed in section 6.2. Finally, in section 6.3, the results are given.

6.1 Approach

In this section the procedure used for adjusting turnover for trading day and seasonal effects is described. The goal was to adjust turnover data of the 1003 companies analysed in chapter 4. Turnover data for period 199301 up to and including 200311 have been used. For 733 of the 1003 companies, all 133 data points were available (around 10% of these values has been estimated because of non response). For 96% of all companies 60 data points or more were available. These figures indicate that the length of turnover time series was sufficient to perform seasonal adjustment. Because data of many companies had to be processed the choice was made to use a semi-automatic procedure. This may not give the best possible seasonal adjustment for each time series, but opens the possibility to adjust the large amount of data. The final quality of the adjustments proved to be good enough for the analysis carried out in the remainder of this paper.

For 1000 of the 1003 companies analysed in chapter 4 seasonal adjustment was possible using the program X12-Arima (U.S. Census Bureau, 2001) in conjunction with the user shell Vivaldi of Statistics Netherlands. An illustration of the procedure used is given in Figure 14.

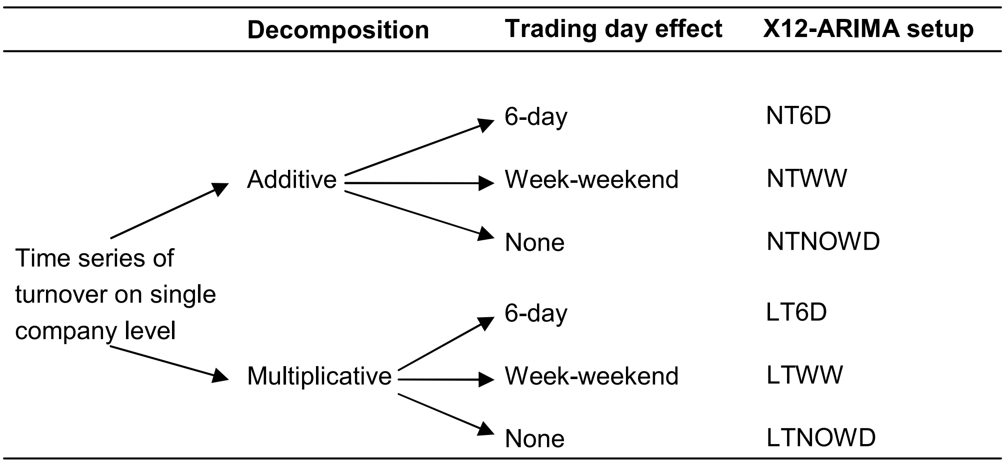

Figure 14. Illustration of the approach to seasonally adjust turnover data.

It is noted that for all setups discussed below, X12-Arima has been instructed to automatically select the ARIMA-model. Options used were: (1) method=best; take the estimated model with the lowest within-sample forecast error (2) mode=forecast; the model is used to produce a year of forecasts.

First, the type of decomposition has been determined for each of the 1000 series. Two main types of decomposition can be performed: additive or multiplicative. The type of decomposition has been selected using an automatic method: X12-Arima performs an automatic analysis and decides which transformation to use. The setup named AOFM used for this first step is given in Appendix E.

Given the decomposition for each series it was possible to pre-process the series by correcting for possible trading day patterns using regression variables. Each company was classified as having (1) a 6-day pattern, (2) a week-weekend pattern or (3) no trading day pattern. For statistical testing a 5% significance level was used. If both the 6-day and the week-weekend pattern were significant, the method with the lowest P-value was selected.

After pre-processing, the actual seasonal adjustment has been carried out using X12-Arima. For all setups the default for the filter has been set by using the Moving Seasonality Ratio (MSR). This means that the final seasonal filter was chosen automatically. The lower and upper sigma limits used to downweight extreme irregular values in the internal seasonal adjustment procedure were set to 1.20 and 2.00, respectively. The six setups named NT6D, NTWW, NTNOWD, LT6D, LTWW and LTNOWD used for this step are given in Appendix E.

Final remark

Leap year effects were only significant for 2% of the companies analysed. In order to limit the number of X12-Arima setups needed to seasonally adjust turnover of all 1000 companies, this correction has not been applied to *any* company, also not to companies for which the effect was significant. Omitting this correction is expected (almost) not to influence the aggregate final results, due to the small number of companies involved.

6.2 Identification of seasonal patterns

In this section the criterion used to assess whether the turnover of a single company has an identifiable seasonal pattern or not is discussed. The quality of a seasonal adjustment is expressed using eleven M-measures generated by X12-Arima. Four important M-measures are given in Table 10.

Table 10. Seasonal adjustment: M-measures.

Measure	Description
M2	The relative contribution of the irregular component to the stationary portion of the variance
M7	The amount of moving seasonality present relative to the amount of stable seasonality
M10	The size of the fluctuations in the seasonal component throughout the last three years
M11	The average linear movement in the seasonal component throughout the last three years.

The value of these measures can range from 0.0 to 3.0. Lower M-measures correspond with a better seasonal adjustment.

The overall quality measure of a seasonal adjustment is calculated as a weighted average of these M-measures. The definitions of Q-measures are given in Table 11.

Table 11. Seasonal adjustment: Q-measures.

Measure	Description
Q	Overall index of the acceptability of the seasonal adjustment
Q2	Q statistic computed without the M2 Quality Measure statistic

Q-measures can range from 0.0 to 3.0, with 0.0 as best performance. For both the individual M- and Q-measures values above 1.0 are best avoided. Generally, the quality of an adjustment is considered reliable if the values of the mentioned measures do not exceed 0.7.

Many subjective aspects play a role to assess if a time series has an identifiable seasonal pattern or not. Often, all the different quality measures are subjectively examined for every processed series. With 1000 series "manual inspection" is not possible. The process to determine if the series have seasonal patterns has to be automated.

This has been achieved by adopting the rule that turnover data of a single company have an identifiable seasonal pattern if $M7<1$ and no identifiable seasonal pattern if $M7\geq1$. The most important reason for this choice is that M7 is the most important M-measure. It has the highest weight in the Q-values.

6.3 Results

In this section, results for seasonally adjusted turnover for the 1000 companies are summarized. First, one remaining error and one remaining warning in the output of X12-Arima are discussed. For the 1000 companies processed for one company the error: "Estimation failed to converge -- maximum function evaluations reached" was reported during the final X12-Arima run. For three companies the warning: "At least one negative value was found in one of the trend cycle estimates" was found in the output. For the four companies involved, the final seasonal adjusted results of turnover were visually inspected. No strange patterns were found. Therefore, the decision has been made to keep these results in the final data set.

Results of the number of companies for each setup are given in Table 12.

Table 12. Number of companies by setup.

Setup	Decomposition	Trading day	Number of companies
NT6D	Additive	6-day	110
NTWW	Additive	Week-weekend	226
NTNOWD	Additive	None	213
LT6D	Multiplicative	6-day	69
LTWW	Multiplicative	Week-weekend	170
LTNOWD	Multiplicative	None	212

Overall, 549 companies have additive and 451 have multiplicative seasonality in their turnover time series. In total, trading day correction is applied for turnover of

575 companies. For 396 companies the week-weekend correction has been used, for 179 companies the 6-day correction. Trading day correction was not necessary for turnover of 425 companies.

In Figure 15, a histogram of the values of M7 belonging to the turnover time series of the 1000 companies is given.

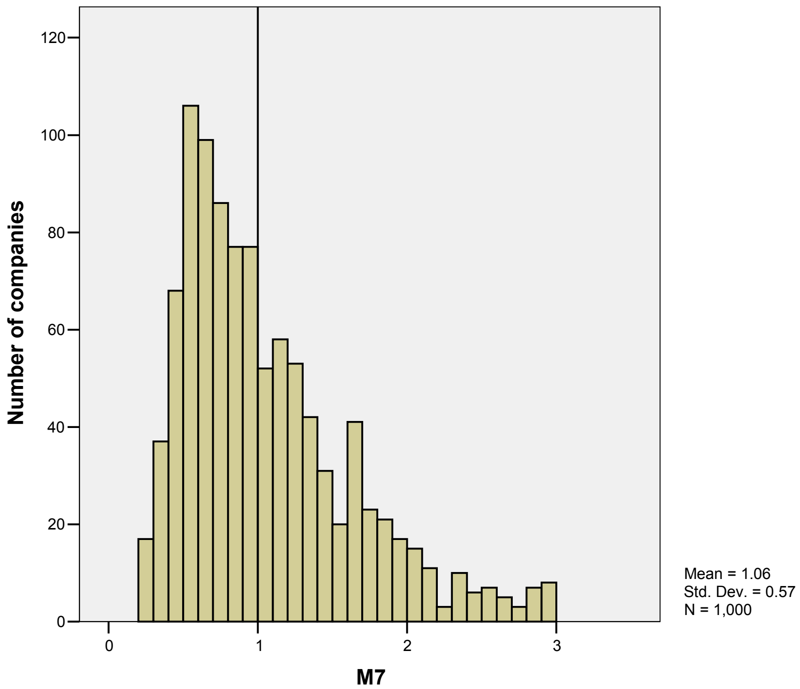

Figure 15. Histogram for M7.

Using the criterion M7<1 defined in section 6.2, 567 of the 1000 companies (56.7%) are identified as having a seasonal pattern in turnover. The remaining 433 companies do not have a seasonal pattern in turnover.

Results for the percentage of companies with and without a seasonal pattern in turnover with a break-up for the 2-digit NACE-level are given in Table 13. Just like in section 4.3, NACE 2-digit groups 16, 18, 19, 23, 30 and 32 are not analysed separately.

Table 13. Percentage of companies with seasonal pattern in turnover. NACE 2-digit levels indicated in grey are excluded from analysis.

NACE 2-digit	Description		Seasonal pattern? Yes	No	Total
15	Food products and beverages	Count	67	57	124
		% within NACE 2-d.	54.0%	46.0%	100.0%
16	Tobacco products	Count	3	3	6
		% within NACE 2-d.	50.0%	50.0%	100.0%
17	Textiles	Count	28	14	42
		% within NACE 2-d.	66.7%	33.3%	100.0%
18	Wearing apparel	Count	11	2	13
		% within NACE 2-d.	84.6%	15.4%	100.0%
19	Leather (and products)	Count	13	2	15
		% within NACE 2-d.	86.7%	13.3%	100.0%
20	Wood (and products)	Count	19	12	31
		% within NACE 2-d.	61.3%	38.7%	100.0%
21	Paper, paperboard (and products)	Count	38	16	54
		% within NACE 2-d.	70.4%	29.6%	100.0%
22	Publishing, printing and reproduction	Count	21	7	28
		% within NACE 2-d.	75.0%	25.0%	100.0%
23	Coke, refined petroleum and nuclear fuel	Count	0	6	6
		% within NACE 2-d.	0.0%	100.0%	100.0%
24	Chemicals (and products)	Count	52	48	100
		% within NACE 2-d.	52.0%	48.0%	100.0%
25	Rubber and plastic products	Count	29	6	35
		% within NACE 2-d.	82.9%	17.1%	100.0%
26	Glass, earthenware, cement, lime and plaster articles	Count	73	8	81
		% within NACE 2-d.	90.1%	9.9%	100.0%
27	Basic metals	Count	29	13	42
		% within NACE 2-d.	69.0%	31.0%	100.0%
28	Fabricated metal products	Count	72	77	149
		% within NACE 2-d.	48.3%	51.7%	100.0%
29	Machinery and equipment	Count	38	82	120
		% within NACE 2-d.	31.7%	68.3%	100.0%
30	Office machinery and computers (*not active in NL*)	Count	3	0	3
		% within NACE 2-d.	100.0%	0.0%	100.0%
31	Other electrical machinery and apparatus	Count	11	16	27
		% within NACE 2-d.	40.7%	59.3%	100.0%
32	Radio, television and communication equipment and apparatus	Count	2	5	7
		% within NACE 2-d.	28.6%	71.4%	100.0%
33	Medical, precision and optical instruments, watches and clocks	Count	10	13	23
		% within NACE 2-d.	43.5%	56.5%	100.0%
34	Motor vehicles, trailers and semi-trailers	Count	20	13	33
		% within NACE 2-d.	60.6%	39.4%	100.0%
35	Other transport equipment	Count	2	27	29
		% within NACE 2-d.	6.9%	93.1%	100.0%
36	Furniture and other manufacturing n.e.c.	Count	26	6	32
		% within NACE 2-d.	81.3%	18.8%	100.0%
Total		Count	567	433	1.000
		% within NACE 2-d.	56.7%	43.3%	100.0%

According to Table 13, NACE 2-digit level 26 (Glass, earthenware, cement, lime and plaster articles) has with 90.1% the highest percentage of companies with a seasonal pattern in turnover, followed by NACE 25 (Rubber and plastic products) with 82.9%. Third is NACE 36 (Furniture and other manufacturing n.e.c.), with 81.3% of the companies having a seasonal pattern in turnover.

Very little seasonal influence in turnover has been found for NACE 2-digit level 35 (Other transport equipment). For only 6.9% of the companies of this branch of industry a seasonal pattern has been detected. In NACE 29 (Machinery and equipment) and 31 (Other electrical machinery and apparatus), respectively 31.7% and 40.7% of the analysed companies has an identifiable seasonal pattern in turnover.

It is noted that for NACE 23 (Coke, refined petroleum and nuclear fuel), although officially not analysed due to a lack of data, 0 out of 6 companies have a seasonal pattern in turnover. This is plausible if it is assumed that these companies use continuous production for their manufacturing process.

Taken on the whole, the results of Table 13 look plausible. They are used for the next step of this paper: assessing the influence of seasonal patterns on the percentage of companies for which turnover results agree with MBS results.

7. Influence of seasonal patterns on classification of companies

This chapter is an extension of section 4.3. In that section single companies were classified into groups A and C according to the correspondence between MBS and turnover data. The influence on these results of the presence or absence of seasonal patterns in turnover of these companies has not been analysed. Here, these effects are investigated. In section 7.1 a 'subset' method is discussed. In section 7.2 the results of a regression method are given. In section 7.3 a comparison between these two methods is made. In section 7.4 the quantitative importance of seasonality on the results for the percentage of companies classified into groups A and C is analysed. Finally, in section 7.5, the relation of the classification with the 'predictive power' of question 1 of the MBS is discussed.

7.1 Subset method

The objective of this section is to analyse the influence of seasonal patterns in turnover on the results for classifying companies into groups A and C. To do this, three subsets of companies and their turnover data have been created:

Subset 1: Company turnover has a seasonal pattern, but *do not correct* for this effect (567 companies)

Subset 2: Company turnover has a seasonal pattern, *correct* for this effect (567 companies)

Subset 3: Company turnover does not have a seasonal pattern (433 companies)

The idea behind this split-up is the following. In section 4.1, the percentage of companies in groups A and C has been calculated by classifying all 1003 companies as one single group. No split-up of companies dependent on the presence or absence of seasonal patterns in turnover has been made. As a result, the percentage of companies in groups A and C are based on a 'mixture' of companies with and without seasonal patterns. This leaves the question whether the results of section 4.1 are contaminated with seasonal patterns.

However, by making groups of companies using the defined subsets, seasonal influences can be analysed. If only subset 3 is used, the percentage of companies classified into groups A and C only relies on the 433 companies without a seasonal pattern in turnover. If only subset 1 is used, the percentage of companies classified into groups A and C is only based on the 567 companies with a seasonal pattern in turnover. Subset 2 makes it possible to analyse the percentage of the 567 companies with a seasonal pattern classified into groups A and C after turnover has been adjusted for these seasonal influences.

Thus, using the three subsets, it is possible to see how seasonal patterns in turnover influence the results presented in section 4.1. The results for classifying companies into groups A and C for the different subsets using the same method as described in section 4.1 is given in Table 14.

Table 14. Percentage of companies classified into group A and C, by subset.

	Group	
	A	C
Section 4.1	35.5	57.6
Subset 1	41.6	62.3
Subset 2	27.9	50.1
Subset 3	27.5	51.7

The percentage of companies classified into group A for subset 1 is 6.1% larger than the percentage of companies classified into group A in section 4.1. The same percentage for subset 3 is 8.0% smaller than for the results of section 4.1. The results for group C are similar. The percentage of companies classified into this group is 62.3% for subset 1 and 51.7% for subset 3.[7] This is 4.7% higher and 5.9% lower than the results of section 4.1.

The results are not surprising. If the turnover of a company has a seasonal pattern, there is a big chance that the MBS data have a similar seasonal pattern. This automatically leads to a better agreement between MBS and turnover data compared to when this seasonal pattern would not be present.

The results of section 4.1 can also be presented as weighed averages of the results for subsets 1 and 3. The fractions of companies in each subset are used as weights.

Group A

$$35.5 = \underbrace{\frac{567}{1000} \cdot 41.6}_{\text{Subset 1}} + \underbrace{\frac{433}{1000} \cdot 27.5}_{\text{Subset 3}}$$

Group C

$$57.6 \cong \underbrace{\frac{567}{1000} \cdot 62.3}_{\text{Subset 1}} + \underbrace{\frac{433}{1000} \cdot 51.7}_{\text{Subset 3}}$$

(0.1%-point round-off error)

In this way, the results of section 4.1 have been ‘decomposed’ into the two subsets. The percentage of companies classified into group A for companies with a seasonal pattern in turnover is 14.1%-point higher than for companies without a seasonal pattern. For group C the results for companies with a seasonal pattern in turnover are 10.6%-point better. Thus, accounting for seasonal effects increases the correspondence between MBS and turnover data.

The results indicate that the agreement of question 1 of the MBS with turnover developments is better for companies with seasonal patterns. This is most probably caused by common seasonal patterns between MBS and turnover data. Comparing results for subset 1, 2 and 3 (see Table 14) exemplifies this idea. For subset 1, the percentage of companies classified into group A is 41.6%. For subset 2, the seasonally adjusted version of subset 1, the percentage of companies classified into group A drops to 27.9%. This is almost equal to the 27.5% for subset 3. Thus, after

[7] The percentages 62.3% and 51.7% are significantly different (χ^2-test, P-value=0.001).

seasonal adjustment, the agreement of question 1 with single company turnover developments on average is the same for all companies.

7.2 Regression method

In this section an alternative for the subset method described in section 7.1 is given. Two data sources are used. The first source is the percentage of companies classified into groups A an C, with breakdown using the NACE 2-digit level. These data have been taken from Table 7 of section 4.3. The second data source is the percentage of companies with a seasonal pattern, also with a breakdown into NACE 2-digit level. These data have been taken from Table 13 of section 6.3. Combined data is given in Table 15. Just like in section 4.3, NACE 2-digit groups 16, 18, 19, 23, 30 and 32 are excluded from analysis because of data shortage.

Table 15. Percentage of companies with seasonal pattern in turnover and percentage of companies classified into groups A and C. Breakdown using the NACE 2-digit level of each company. NACE 2-digit levels indicated in grey are excluded from analysis.

NACE 2-digit	Percentage of companies with seasonal pattern in turnover	Percentage of companies in group	
		A	C
15	54.0	41.1	65.3
16	50.0	16.7	33.3
17	66.7	23.8	57.1
18	84.6	23.1	38.5
19	86.7	33.3	46.7
20	61.3	22.6	48.4
21	70.4	51.9	66.7
22	75.0	60.7	71.4
23	0.0	50.0	66.7
24	52.0	44.0	62.0
25	82.9	37.1	60.0
26	90.1	28.0	57.3
27	69.0	38.1	57.1
28	48.3	36.9	58.4
29	31.7	29.5	48.4
30	100.0	0.0	0.0
31	40.7	22.2	55.6
32	28.6	14.3	28.6
33	43.5	47.8	69.6
34	60.6	24.2	54.5
35	6.9	17.2	41.4
36	81.3	40.6	65.6

Graphs of the percentage of companies in group A or C plotted against the percentage of companies with seasonal pattern in turnover are given in Figure 16 and Figure 17, respectively.

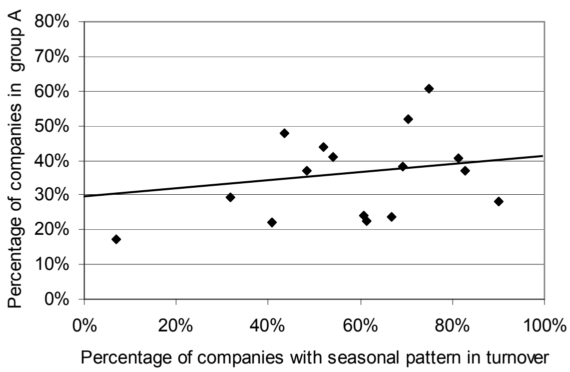

Figure 16. Percentage of companies in group A as a function of the percentage of companies with a seasonal pattern in turnover. Including regression line, calculated without leverage point (6.9; 17.2).

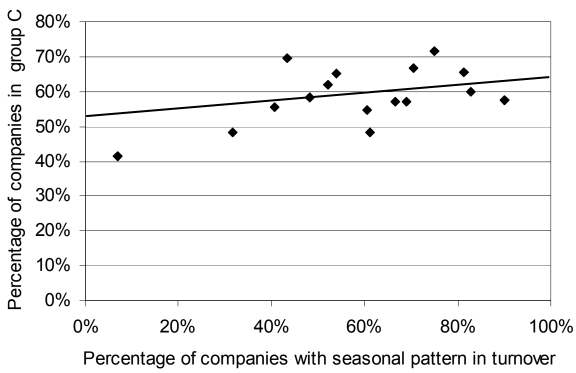

Figure 17. Percentage of companies in group C as a function of the percentage of companies with a seasonal pattern in turnover. Including regression line, calculated without leverage point (6.9; 41.4).

On average, if the percentage of companies with a seasonal pattern in a NACE 2-digit level increases, also the percentage of companies classified in group A or C increases. Assuming a linear relationship for this effect, linear regression has been performed. The resulting line has been graphed in Figure 16 and Figure 17. The points (6.9; 17.2) and (6.9; 41.4) have been omitted, because they are considered leverage points. The equations for the two regression lines are:

$$\%(\text{Group A})=0.1172 \cdot \%(\text{Companies with Seasonal Pattern})+29.33\% \quad (R^2=0.029)$$

$$\%(\text{Group C})=0.1130 \cdot \%(\text{Companies with Seasonal Pattern})+52.84\% \quad (R^2=0.075)$$

Substituting %(Companies with Seasonal Pattern)=0 gives an estimation for the number op companies classified into group A and C if all companies would not have a seasonal pattern in turnover. For group A the result is 29.3%, for group C 52.8%. Substituting %(Companies with Seasonal Pattern) =100%, the results with seasonal patterns in turnover for group A and C are 41.1% and 64.1%, respectively. In the next section these results are compared with the results of section 7.1.

7.3 Comparison of subset and regression method

In this section results obtained in sections 7.1 and 7.2 are compared. The results for group A are given in Table 16.

Table 16. Comparison of subset and regression method for group A.

	Percentage of companies in group A using		
Seasonal pattern?	Subset method	Regression method	Difference
Yes	41.6	41.1	0.5
No	27.5	29.3	-1.8

The difference between the percentages of companies with seasonal pattern in turnover classified into group A using the two different methods is 0.5%-point. For companies without seasonal pattern in turnover the difference is -1.8%-points.

Results for group C are given in Table 17.

Table 17. Comparison of subset and regression method for group C.

Seasonal pattern?	Percentage of companies in group C using		Difference
	Subset method	Regression method	
Yes	62.3	64.1	-1.8
No	51.7	52.8	-1.1

The difference between the percentages of companies with seasonal pattern in turnover classified into group C using the two different methods is -1.8%-points. For companies without seasonal pattern in turnover the difference is -1.1%-points.

The differences between the subset and the regression method are small. This underpins that the quality of the results is good. Two different methods give almost the same answers.

For the remainder of this paper, the results of the subset method will be used. Doing this, the following final conclusion is reached. For companies with a seasonal pattern in turnover, 41.6% is classified into group A. For companies without seasonal patterns this percentage is 27.5%. For group C, the percentages are 62.3% and 51.7%, respectively.

Thus, looking at the results for group A, the percentage of companies with a seasonal pattern in turnover for which turnover is in agreement with question 1 of the MBS is 14.1% higher than the same percentage for companies without a seasonal pattern in turnover. For group C, this percentage is 10.6%

7.4 Influence of the seasonal components

Until now, only a distinction into companies with or without a seasonal pattern in turnover has been made. In this section, the influence of the magnitude of the seasonal component in turnover on the percentage of companies classified into groups A and C is analysed. The importance of seasonal components is expressed by M7 (see section 6.2). The lower the value of M7, the higher the amount of seasonality in the processed series is; the higher, the less seasonal pattern.

To do the analysis, companies have been divided into 9 ‘bins’ using the size of their value of M7. Each bin contains 110, 111 or 112 companies. The percentage of companies classified into groups A and C has been calculated. Scatter plots of these results against the M7 value of the middle of the bins are given in Figure 18 and Figure 19.

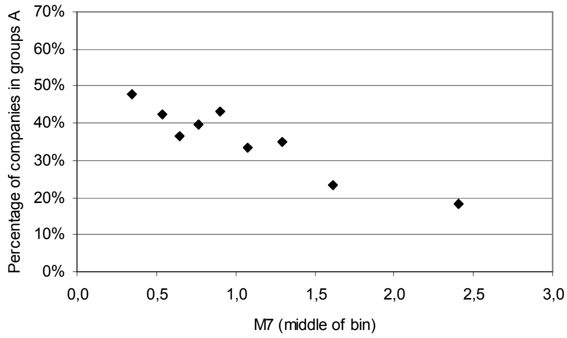

Figure 18. Percentage of companies classified into group A as a function of M7.

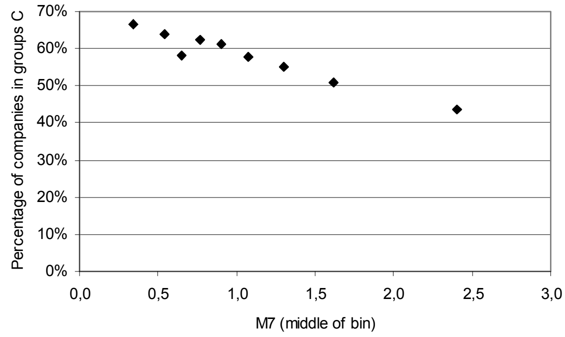

Figure 19. Percentage of companies classified into group C as a function of M7.

Generally, the lower the value of M7, the higher the percentage of companies classified into groups A and C. The higher the value of M7, the lower the percentage of companies classified into groups A and C. Thus, on average, the stronger the seasonal pattern in turnover of a single company, the better question 1 of the MBS is in agreement with this turnover.

7.5 'Predictive power' of question 1 of the MBS

In this section the 'predictive power' of the MBS is discussed using the classification of companies without seasonal pattern in turnover (subset 3) as an example. For a correct analysis, it is necessary to return to the 7-category classification (see section 3.4). The results of applying this classification for subset 3 are given in Table 18.

Table 18. Results for classifying companies of subset 3 using question 1.

	Category							Total
	1	2	3	4	5	6	7	
Count	119	44	6	52	60	55	97	433
% of total	27.5%	10.2%	1.4%	12.0%	13.9%	12.7%	22.4%	100.0%

Group C is defined as the sum of categories 1, 2, 3 and 6. Category 4 is the group of companies which *always* answer "remained the same", Category 5 is the group where companies give logical ordered answers, but the bias is not known. Category 7 contains all companies without "logically ordered answers".

The 51.7% of companies classified in group C has been calculated as follows:

$$\%\ in\ group\ C = \frac{No.\ of\ companies\ classified\ into\ categories\ 1, 2, 3\ and\ 6}{No.\ of\ companies\ classified\ into\ categories\ 1, 2, 3, 4, 5, 6\ and\ 7} * 100\%$$

Now, it is tempting to apply the following line of thought. "51.7% of the companies of subset 3 give useful answers to question 1. If all these 433 companies would give random answers to question 1, the number of companies theoretically classified into group C would be 50.0%. Therefore, question 1 of the MBS performs 1.7% better than random answers".

This line of thought is erroneous, because it is known that the 52 companies classified into category 4 certainly give strongly biased answers. They *always* answer “remained the same”, for all months studied. In section 4.1, it was even questioned if these companies are “lazy” in answering question 1 of the MBS and try to finish the questionnaire fast. These companies maybe do not try to give good indications for turnover developments. For this reason, it seems better to exclude category 4 totally from analysis when estimating the ‘predictive power’ of question 1. This leads to the following definition:

$$'predictive\ power' = \frac{No.\ of\ companies\ classified\ into\ categories\ 1, 2, 3\ and\ 6}{No.\ of\ companies\ classified\ into\ categories\ 1, 2, 3, 5, 6\ and\ 7} * 100\%$$

The ‘predictive power’ for different sets of companies is given in Table 19.

Table 19. ‘Predictive power’ of question 1.

	‘Predictive power’
Section 4.1	64.7%
Subset 1	69.2%
Subset 3	58.8%

For subset 3 the ‘predictive power’ is 58.8%. This is 8.8% better than random answers. For companies with a seasonal pattern in turnover (subset 1) the ‘predictive power’ is 19.2% higher than pure guesses. For the results of section 4.1 the ‘predictive power’ of question 1 is 64.7%. This is 15.7% higher than random answers.

Thus, the ‘predictive power’ of question 1 is influenced by seasonal patterns. The ‘predictive power’ of question 1 is higher when companies have seasonal patterns in turnover.

8. Conclusions

In this chapter, the conclusions of this paper are presented and some final remarks are given.

8.1 Conclusions

- A classification has been developed to determine to which extent the answers of individual companies to the Manufacturing Business Sentiment Survey data relate to Turnover data. This classification can be used for:
    - quality assessment of MBS data on individual company level
    - quantifying Business Survey data.
- Turnover data of single companies has been seasonally adjusted with a semi-automatic procedure using X12-Arima. 57% of the companies have a seasonal pattern in turnover.
- Of all classified companies, 35.5% give “logical” and unbiased answers to question 1 (“recent production”) of the MBS. For the subset of companies with a seasonal pattern in turnover this percentage is 41.6%; for the subset of companies without a seasonal pattern it is 27.5%.
- 19.6% of the companies answer completely illogical to question 1 and 11.0% answer “remained the same” for a longer period of time.
- Of all classified companies, if only balances are calculated and bias correction is applied, on average 57.6% of the companies give useful answers to question 1 of the MBS. For the subset of companies with a seasonal pattern in turnover this percentage is 62.3%; for the subset of companies without a seasonal pattern in turnover it is 51.7%.
- The level of agreement between question 1 of the MBS and turnover partly resides in seasonal patterns. On average, the stronger the seasonal pattern in turnover of a single company, the better question 1 of the MBS is in agreement with this turnover development.
- Excluding companies that always answer “remained the same” from the calculations, the ‘predictive power’ of companies with a seasonal pattern in turnover is 69.2%. For companies without a seasonal pattern in turnover, the ‘predictive power’ is 58.8%. This is respectively 19.2% and 8.8% better than if answers of companies to question 1 would be completely random.
- Of all classified companies, 26.6% give “logical” and unbiased answers to question 2 (“production expectations”) of the MBS. 27.5% of the companies answer completely illogical to question 2 and 12.6% answer “remain the same” for a longer period of time.

- Of all classified companies, if only balances are calculated and bias correction is applied, on average 46.6% of the companies give useful answers to question 2 of the MBS.
- The time shift in relation to turnover data of the answers to question 1 of the MBS is, in general, in agreement with the time shift that the phrasing of the question suggests. The same conclusion is drawn for question 2.
- Companies, in general, are better at assessing the recent past than predicting the near future.

8.2 Remarks

- For different size classes, it seems that the size of the company has practically no influence on its capacity to correctly assess the direction of turnover development at the time the MBS is held.
- Specific NACE 2-digit groups seem better at assessing the past than others.
- Regarding question 2 of the MBS, it is not clear if the persons answering to the MBS are capable of predicting turnover (benchmark for production) three months ahead. This topic could be investigated more in depth.

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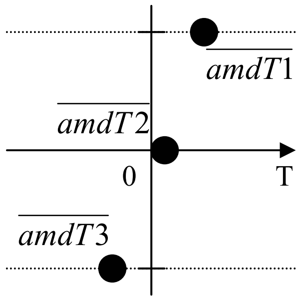
Appendix A. Cases

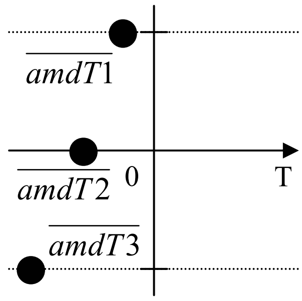
This appendix contains a description of all cases defined for the classification developed in chapter 3.

123_FS123_NOBIASMBS



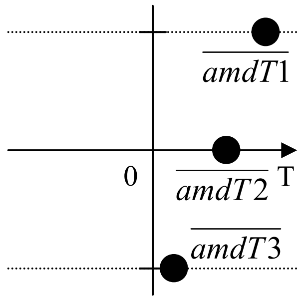
($\overline{amdT1} > \overline{amdT2}$) and ($\overline{amdT2} > \overline{amdT3}$)
$\overline{amdT1}$ >0 and $\overline{amdT3}$ <0

123_FS123_POSBIASMBS



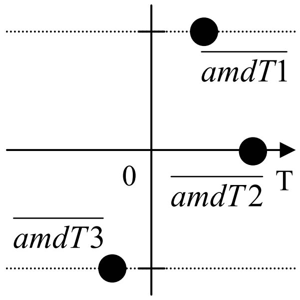
($\overline{amdT1} > \overline{amdT2}$) and ($\overline{amdT2} > \overline{amdT3}$)
$\overline{amdT1}$ <= 0

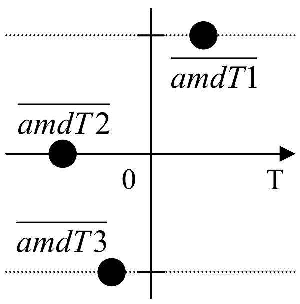
123_FS123_NEGBIASMBS



($\overline{amdT1} > \overline{amdT2}$) and ($\overline{amdT2} > \overline{amdT3}$)
$\overline{amdT3}$ >=0

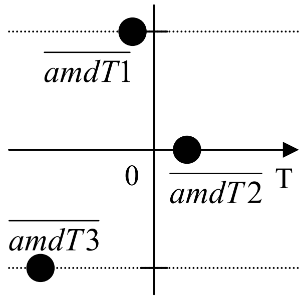
123_FS13_NOBIASMBS

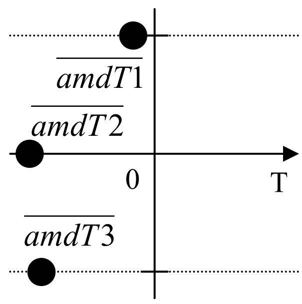




$\overline{amdT1} > \overline{amdT3}$ and ($\overline{amdT2}$ <= $\overline{amdT3}$ or $\overline{amdT2}$ >= $\overline{amdT1}$)
$\overline{amdT1}$ >0 and $\overline{amdT3}$ <0

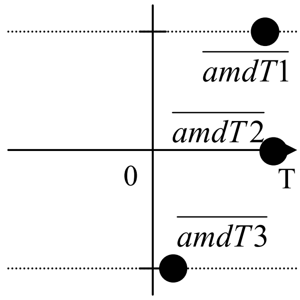
123_FS13_POSBIASMBS

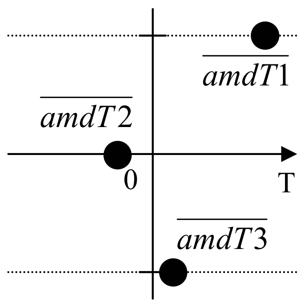




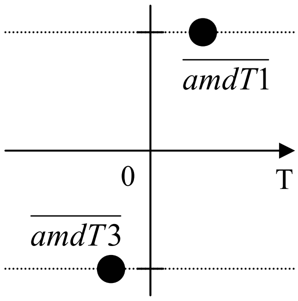
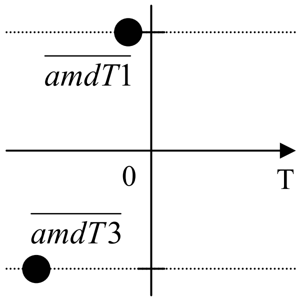
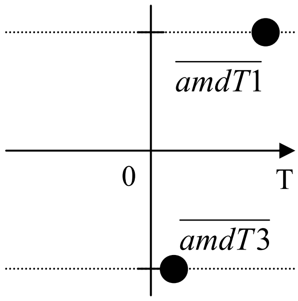
$\overline{amdT1} > \overline{amdT3}$ and ($\overline{amdT2}$ <= $\overline{amdT3}$ or $\overline{amdT2}$ >= $\overline{amdT1}$)
$\overline{amdT1}$ <= 0

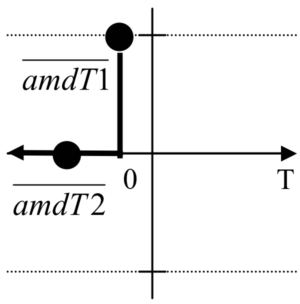
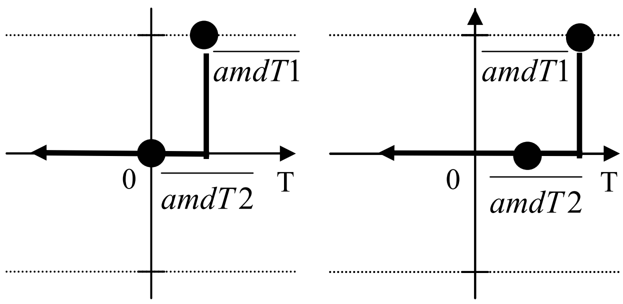
123_FS13_NEGBIASMBS

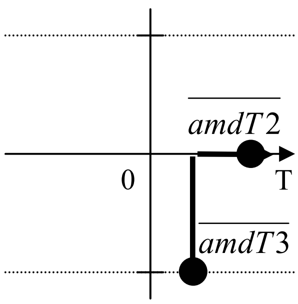
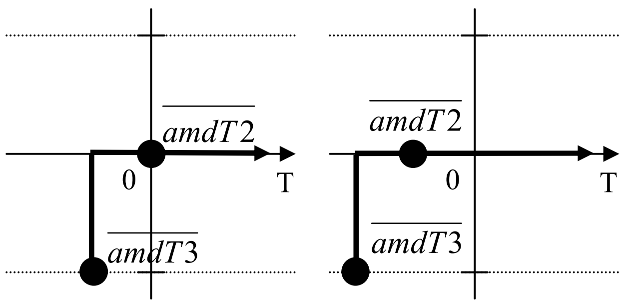


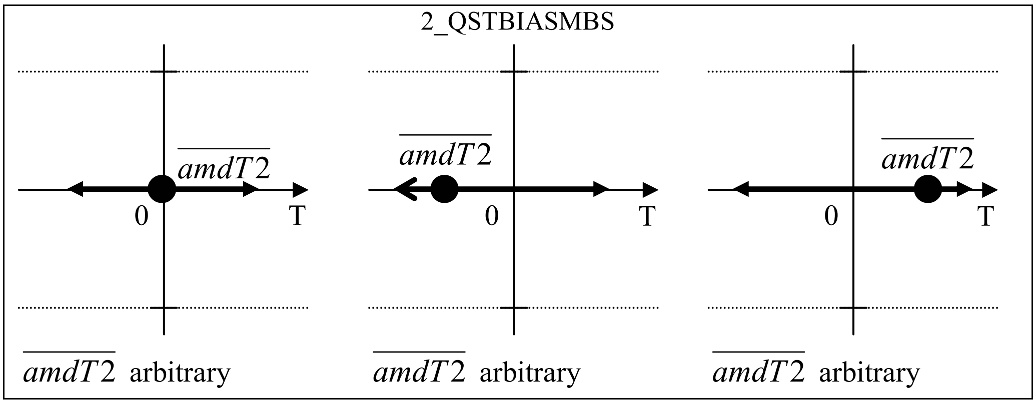


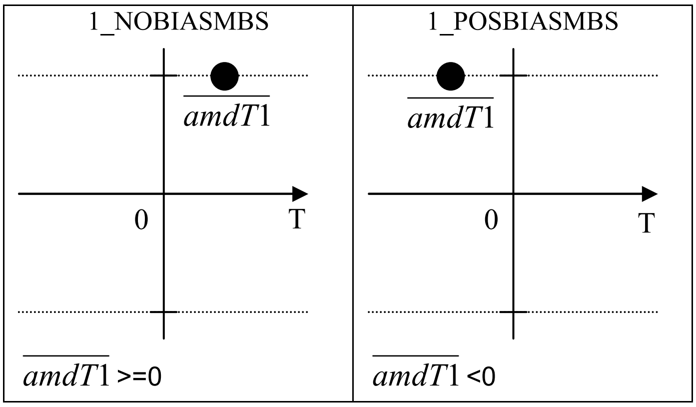
$\overline{amdT1} > \overline{amdT3}$ and ($\overline{amdT2}$ <= $\overline{amdT3}$ or $\overline{amdT2}$ >= $\overline{amdT1}$)
$\overline{amdT3}$ >=0

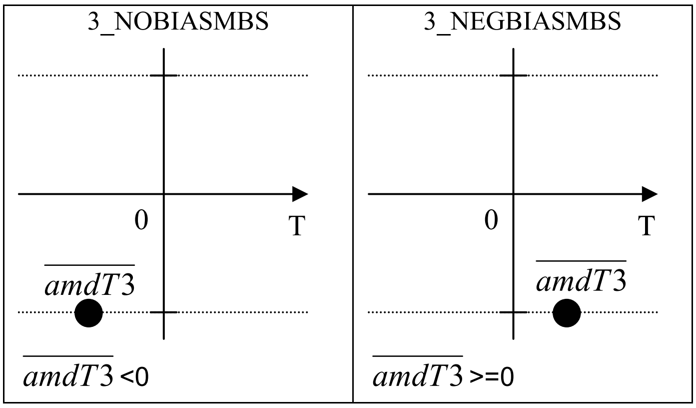
13_FS13_NOBIASMBS	13_FS13_POSBIASMBS	13_FS13_NEGBIASMBS
		
$\overline{amdT1} > \overline{amdT3}$ $\overline{amdT1}$ >0 and $\overline{amdT3}$ <0	$\overline{amdT1} > \overline{amdT3}$ $\overline{amdT1}$ <= 0	$\overline{amdT1} > \overline{amdT3}$ $\overline{amdT3}$ >=0

12_O1>O2_POSBIASMBS	12_O1>O2_QSTBIASMBS	
		
$\overline{amdT1} > \overline{amdT2}$ and $\overline{amdT1}$ <=0	$\overline{amdT1} > \overline{amdT2}$ and $\overline{amdT1}$ >0	$\overline{amdT1} > \overline{amdT2}$ and $\overline{amdT1}$ >0

23_O3<O2_NEGBIASMBS	23_O3<O2_QSTBIASMBS	
		
$\overline{amdT2} > \overline{amdT3}$ and $\overline{amdT3}$ >=0	$\overline{amdT2} > \overline{amdT3}$ and $\overline{amdT3}$ <0	$\overline{amdT2} > \overline{amdT3}$ and $\overline{amdT3}$ <0


2_QSTBIASMBS
$\overline{amdT2}$
0
T
$\overline{amdT2}$ arbitrary
$\overline{amdT2}$ arbitrary
$\overline{amdT2}$ arbitrary


1_NOBIASMBS
1_POSBIASMBS
$\overline{amdT1}$
0
T
$\overline{amdT1}$ >=0
$\overline{amdT1}$ <0


3_NOBIASMBS
3_NEGBIASMBS
$\overline{amdT3}$
0
T
$\overline{amdT3}$ <0
$\overline{amdT3}$ >=0

Appendix B. Detailed results for question 1

This appendix contains the results of classifying companies using question 1 of the MBS into the 7-category classification developed in chapter 3. Table 20 contains the results for a breakdown using size class and Table 21 contains the results for a breakdown using NACE 2-digit level.

Table 20. Size class * category cross tabulation.

			Category							Total
			1	2	3	4	5	6	7	
Size class	5	Count	65	13	4	26	33	19	32	192
		% within size class	33.9%	6.8%	2.1%	13.5%	17.2%	9.9%	16.7%	100.0%
	6	Count	73	19	2	27	27	28	52	228
		% within size class	32.0%	8.3%	.9%	11.8%	11.8%	12.3%	22.8%	100.0%
	7	Count	93	26	2	25	28	33	48	255
		% within size class	36.5%	10.2%	.8%	9.8%	11.0%	12.9%	18.8%	100.0%
	8	Count	90	21	3	16	17	27	42	216
		% within size class	41.7%	9.7%	1.4%	7.4%	7.9%	12.5%	19.4%	100.0%
	9	Count	35	10	0	16	13	15	23	112
		% within size class	31.3%	8.9%	.0%	14.3%	11.6%	13.4%	20.5%	100.0%
Total		Count	356	89	11	110	118	122	197	1003
		% within size class	35.5%	8.9%	1.1%	11.0%	11.8%	12.2%	19.6%	100.0%

Table 21. NACE 2-digit * category cross tabulation. Groups with less than 20 companies are indicated in grey.

			Category							Total
			1	2	3	4	5	6	7	
NACE 2-digit	15	Count	51	9	1	9	9	20	25	124
		% within NACE 2-d.	41.1%	7.3%	.8%	7.3%	7.3%	16.1%	20.2%	100.0%
	16	Count	1	0	0	1	1	1	2	6
		% within NACE 2-d.	16.7%	.0%	.0%	16.7%	16.7%	16.7%	33.3%	100.0%
	17	Count	10	6	0	0	7	8	11	42
		% within NACE 2-d.	23.8%	14.3%	.0%	.0%	16.7%	19.0%	26.2%	100.0%
	18	Count	3	1	0	3	2	1	3	13
		% within NACE 2-d.	23.1%	7.7%	.0%	23.1%	15.4%	7.7%	23.1%	100.0%
	19	Count	5	1	1	3	1	0	4	15
		% within NACE 2-d.	33.3%	6.7%	6.7%	20.0%	6.7%	.0%	26.7%	100.0%
	20	Count	7	3	1	3	5	4	8	31
		% within NACE 2-d.	22.6%	9.7%	3.2%	9.7%	16.1%	12.9%	25.8%	100.0%
	21	Count	28	4	0	5	7	4	6	54
		% within NACE 2-d.	51.9%	7.4%	.0%	9.3%	13.0%	7.4%	11.1%	100.0%
	22	Count	17	3	0	0	1	0	7	28
		% within NACE 2-d.	60.7%	10.7%	.0%	.0%	3.6%	.0%	25.0%	100.0%
	23	Count	3	1	0	0	0	0	2	6
		% within NACE 2-d.	50.0%	16.7%	.0%	.0%	.0%	.0%	33.3%	100.0%
	24	Count	44	8	0	13	10	10	15	100
		% within NACE 2-d.	44.0%	8.0%	.0%	13.0%	10.0%	10.0%	15.0%	100.0%
	25	Count	13	4	0	2	4	4	8	35
		% within NACE 2-d.	37.1%	11.4%	.0%	5.7%	11.4%	11.4%	22.9%	100.0%
	26	Count	23	6	1	9	9	17	17	82
		% within NACE 2-d.	28.0%	7.3%	1.2%	11.0%	11.0%	20.7%	20.7%	100.0%
	27	Count	16	3	1	6	6	4	6	42
		% within NACE 2-d.	38.1%	7.1%	2.4%	14.3%	14.3%	9.5%	14.3%	100.0%
	28	Count	55	15	2	19	15	15	28	149
		% within NACE 2-d.	36.9%	10.1%	1.3%	12.8%	10.1%	10.1%	18.8%	100.0%
	29	Count	36	8	2	17	24	13	22	122
		% within NACE 2-d.	29.5%	6.6%	1.6%	13.9%	19.7%	10.7%	18.0%	100.0%
	30	Count	0	0	0	0	1	0	2	3
		% within NACE 2-d.	.0%	.0%	.0%	.0%	33.3%	.0%	66.7%	100.0%
	31	Count	6	2	0	4	2	7	6	27
		% within NACE 2-d.	22.2%	7.4%	.0%	14.8%	7.4%	25.9%	22.2%	100.0%
	32	Count	1	1	0	1	3	0	1	7
		% within NACE 2-d.	14.3%	14.3%	.0%	14.3%	42.9%	.0%	14.3%	100.0%
	33	Count	11	3	0	1	3	2	3	23
		% within NACE 2-d.	47.8%	13.0%	.0%	4.3%	13.0%	8.7%	13.0%	100.0%
	34	Count	8	3	0	6	4	7	5	33
		% within NACE 2-d.	24.2%	9.1%	.0%	18.2%	12.1%	21.2%	15.2%	100.0%
	35	Count	5	3	2	6	2	2	9	29
		% within NACE 2-d.	17.2%	10.3%	6.9%	20.7%	6.9%	6.9%	31.0%	100.0%
	36	Count	13	5	0	2	2	3	7	32
		% within NACE 2-d.	40.6%	15.6%	.0%	6.3%	6.3%	9.4%	21.9%	100.0%
Total		Count	356	89	11	110	118	122	197	1003
		% within NACE 2-d.	35.5%	8.9%	1.1%	11.0%	11.8%	12.2%	19.6%	100.0%

Appendix C. Detailed results for question 2

This appendix contains the results of classifying companies using question 2 of the MBS into the 7-category classification developed in chapter 3. Table 22 contains the results for a breakdown using size class and Table 23 contains the results for a breakdown using NACE 2-digit level.

Table 22. Size class * category cross tabulation.

			Category							Total
			1	2	3	4	5	6	7	
Size class	5	Count	41	12	2	26	40	19	49	189
		% within size class	21.7%	6.3%	1.1%	13.8%	21.2%	10.1%	25.9%	100.0%
	6	Count	69	12	2	25	23	21	67	219
		% within size class	31.5%	5.5%	.9%	11.4%	10.5%	9.6%	30.6%	100.0%
	7	Count	67	26	3	29	32	29	66	252
		% within size class	26.6%	10.3%	1.2%	11.5%	12.7%	11.5%	26.2%	100.0%
	8	Count	57	15	2	24	23	29	60	210
		% within size class	27.1%	7.1%	1.0%	11.4%	11.0%	13.8%	28.6%	100.0%
	9	Count	27	6	0	20	14	16	28	111
		% within size class	24.3%	5.4%	.0%	18.0%	12.6%	14.4%	25.2%	100.0%
Total		Count	261	71	9	124	132	114	270	981
		% within size class	26.6%	7.2%	.9%	12.6%	13.5%	11.6%	27.5%	100.0%

Table 23. NACE 2-digit * category cross tabulation. Groups with less than 20 companies are indicated in grey.

			Category							Total
			1	2	3	4	5	6	7	
NACE 2-digit	15	Count	40	7	3	11	14	12	35	122
		% within NACE 2-d.	32.8%	5.7%	2.5%	9.0%	11.5%	9.8%	28.7%	100.0%
	16	Count	0	1	0	2	2	0	1	6
		% within NACE 2-d.	.0%	16.7%	.0%	33.3%	33.3%	.0%	16.7%	100.0%
	17	Count	10	2	1	3	11	4	10	41
		% within NACE 2-d.	24.4%	4.9%	2.4%	7.3%	26.8%	9.8%	24.4%	100.0%
	18	Count	0	2	0	3	1	2	6	14
		% within NACE 2-d.	.0%	14.3%	.0%	21.4%	7.1%	14.3%	42.9%	100.0%
	19	Count	2	2	0	3	2	1	4	14
		% within NACE 2-d.	14.3%	14.3%	.0%	21.4%	14.3%	7.1%	28.6%	100.0%
	20	Count	11	3	0	1	6	5	4	30
		% within NACE 2-d.	36.7%	10.0%	.0%	3.3%	20.0%	16.7%	13.3%	100.0%
	21	Count	13	3	0	5	9	6	18	54
		% within NACE 2-d.	24.1%	5.6%	.0%	9.3%	16.7%	11.1%	33.3%	100.0%
	22	Count	8	3	0	1	2	9	5	28
		% within NACE 2-d.	28.6%	10.7%	.0%	3.6%	7.1%	32.1%	17.9%	100.0%
	23	Count	3	0	0	1	1	0	1	6
		% within NACE 2-d.	50.0%	.0%	.0%	16.7%	16.7%	.0%	16.7%	100.0%
	24	Count	26	6	0	19	16	9	22	98
		% within NACE 2-d.	26.5%	6.1%	.0%	19.4%	16.3%	9.2%	22.4%	100.0%
	25	Count	10	1	1	2	7	6	7	34
		% within NACE 2-d.	29.4%	2.9%	2.9%	5.9%	20.6%	17.6%	20.6%	100.0%
	26	Count	23	12	1	9	7	6	21	79
		% within NACE 2-d.	29.1%	15.2%	1.3%	11.4%	8.9%	7.6%	26.6%	100.0%
	27	Count	11	3	0	5	5	6	11	41
		% within NACE 2-d.	26.8%	7.3%	.0%	12.2%	12.2%	14.6%	26.8%	100.0%
	28	Count	34	9	2	21	17	16	46	145
		% within NACE 2-d.	23.4%	6.2%	1.4%	14.5%	11.7%	11.0%	31.7%	100.0%
	29	Count	32	7	0	20	16	9	33	117
		% within NACE 2-d.	27.4%	6.0%	.0%	17.1%	13.7%	7.7%	28.2%	100.0%
	30	Count	0	0	0	0	1	0	2	3
		% within NACE 2-d.	.0%	.0%	.0%	.0%	33.3%	.0%	66.7%	100.0%
	31	Count	4	1	0	3	4	7	9	28
		% within NACE 2-d.	14.3%	3.6%	.0%	10.7%	14.3%	25.0%	32.1%	100.0%
	32	Count	2	1	0	1	0	0	4	8
		% within NACE 2-d.	25.0%	12.5%	.0%	12.5%	.0%	.0%	50.0%	100.0%
	33	Count	3	3	1	2	3	3	8	23
		% within NACE 2-d.	13.0%	13.0%	4.3%	8.7%	13.0%	13.0%	34.8%	100.0%
	34	Count	12	1	0	4	3	3	9	32
		% within NACE 2-d.	37.5%	3.1%	.0%	12.5%	9.4%	9.4%	28.1%	100.0%
	35	Count	6	0	0	6	2	4	8	26
		% within NACE 2-d.	23.1%	.0%	.0%	23.1%	7.7%	15.4%	30.8%	100.0%
	36	Count	11	4	0	2	3	6	6	32
		% within NACE 2-d.	34.4%	12.5%	.0%	6.3%	9.4%	18.8%	18.8%	100.0%
Total		Count	261	71	9	124	132	114	270	981
		% within NACE 2-d.	26.6%	7.2%	.9%	12.6%	13.5%	11.6%	27.5%	100.0%

Appendix D. Comparison of classification methods for question 2

This appendix contains the results of a comparison of classifying companies for question 2 of the MBS with respectively $amdT_{BEID,t}$ and $mean(T_{BEID,t} + T_{BEID,t+1} + T_{BEID,t+2}) - T_{BEID,t-1}$ ($amdT'_{BEID,t}$). Results are shown for both a breakdown into size class and NACE 2-digit level. The results for the breakdown into size class are given in Table 24.

Table 24. Comparison for classifying companies for question 2 using respectively $amdT_{BEID,t}$ and $amdT'_{BEID,t}$. Breakdown into size class.

		% classified in group using $amdT_{BEID,t}$			% classified in group Using $amdT'_{BEID,t}$			Difference		
		A	B	C	A	B	C	A	B	C
Size class	5	21.7	22.8	39.2	22.6	24.2	41.4	-0.9	-1.4	-2.2
	6	31.5	32.4	47.5	28.2	30.5	50.7	3.3	1.9	-3.2
	7	26.6	27.8	49.6	29.3	31.3	49.2	-2.7	-3.5	0.4
	8	27.1	28.1	49.0	31.5	31.5	51.7	-4.4	-3.4	-2.7
	9	24.3	24.3	44.1	23.4	24.3	43.0	1.0	0.0	1.2
	total	26.6	27.5	46.4	27.5	29.0	47.9	-0.9	-1.5	-1.5

When results for different size classes are considered, there is no clear indication which classification method gives better results. Regarding the breakdown for classification groups A and C, for two of the five size classes the percentage of companies classified using $amdT_{BEID,t}$ is larger than the percentage using $amdT'_{BEID,t}$. However, it has to be remarked that overall there is a small preference for using $amdT'_{BEID,t}$, because the difference of the percentage of companies classified into categories A and C for total industry is respectively -0.9% and -1.5%.

The results for the breakdown into the NACE 2-digit level are given in Table 25.

Table 25. Comparison for classifying companies for question 2 using respectively $amdT_{BEID,t}$ and $amdT'_{BEID,t}$. Breakdown into NACE 2-digit level.

	% classified in group using $amdT_{BEID,t}$			% classified in group using $amdT'_{BEID,t}$			Difference		
	A	B	C	A	B	C	A	B	C
NACE 2-digit 15	32.8	35.2	50.8	30.8	32.5	52.5	2.0	2.7	-1.7
16	0.0	0.0	16.7	16.7	16.7	16.7	-16.7	-16.7	0.0
17	24.4	26.8	41.5	17.5	20.0	40.0	6.9	6.8	1.5
18	0.0	0.0	28.6	0.0	7.7	30.8	0.0	-7.7	-2.2
19	14.3	14.3	35.7	15.4	23.1	30.8	-1.1	-8.8	4.9
20	36.7	36.7	63.3	34.5	37.9	69.0	2.2	-1.3	-5.6
21	24.1	24.1	40.7	21.2	21.2	42.3	2.9	2.9	-1.6
22	28.6	28.6	71.4	46.4	46.4	75.0	-17.9	-17.9	-3.6
23	50.0	50.0	50.0	50.0	50.0	50.0	0.0	0.0	0.0
24	26.5	26.5	41.8	25.0	26.0	43.8	1.5	0.5	-1.9
25	29.4	32.4	52.9	41.2	41.2	58.8	-11.8	-8.8	-5.9
26	29.1	30.4	53.2	34.6	34.6	57.7	-5.5	-4.2	-4.5
27	26.8	26.8	48.8	30.0	35.0	55.0	-3.2	-8.2	-6.2
28	23.4	24.8	42.1	26.4	27.1	43.1	-2.9	-2.3	-1.0
29	27.4	27.4	41.0	24.6	24.6	40.4	2.8	2.8	0.7
30	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
31	14.3	14.3	42.9	16.0	16.0	32.0	-1.7	-1.7	10.9
32	25.0	25.0	37.5	28.6	28.6	57.1	-3.6	-3.6	-19.6
33	13.0	17.4	43.5	33.3	38.1	52.4	-20.3	-20.7	-8.9
34	37.5	37.5	50.0	32.3	35.5	54.8	5.2	2.0	-4.8
35	23.1	23.1	38.5	11.1	11.1	25.9	12.0	12.0	12.5
36	34.4	34.4	65.6	35.7	42.9	67.9	-1.3	-8.5	-2.2
total	26.6	27.5	46.4	27.5	29.0	47.9	-0.9	-1.5	-1.5

For 8 of the 16 analysed NACE 2-digit levels the percentage of companies classified into group A is larger using $amdT_{BEID,t}$, indicating that there is no clear sign which classification method gives better results. When group C is analysed, for only 4 of the 16 NACE 2-digit levels the percentage of companies classified using $amdT_{BEID,t}$ is larger. This indicates a preference for classifying companies using $amdT'_{BEID,t}$.

Overall, there seems to be a small preference to use $amdT'_{BEID,t}$ for classifying companies for question 2 of the MBS. However, the results presented in this appendix indicate, that there are size classes and NACE 2-digit groups for which using $amdT_{BEID,t}$ gives better results. To determine how the results of question 2 *exactly* have to be interpreted in practice remains a topic for future research.

Appendix E. X12-ARIMA Setups

```
SERIES{
        title = "AOFM"
        Format = "DateValue"
        Period = 12
        File = "d:\temp\vivaldi\10000232.DAT"
        name = "100002"
        precision = 0
        decimals = 0
}
TRANSFORM{
        Function = auto
        adjust = none
        savelog=atr
}
AUTOMDL{
        file = "\\mspv1f\Programma1\ImplSTS\Seizoen\VivX12\VIVW2K\x12\x12a.mdl"
        mode = fcst
        method = best
        Identify = first
}
```

```
SERIES{
        title = "NTLY"
        Format = "DateValue"
        Period = 12
        File = "d:\temp\vivaldi\10000232.DAT"
        name = "100002"
        precision = 0
        decimals = 0
}
TRANSFORM{
        Function = none
        adjust = none
        savelog=atr
}
REGRESSION{
        Variables =(
        lpyear
        )
        save = (ao ls td )
}
AUTOMDL{
        file = "\\mspv1f\Programma1\ImplSTS\Seizoen\VivX12\VIVW2K\x12\x12a.mdl"
        mode = fcst
        method = best
        Identify = first
}
ESTIMATE{
        maxiter = 999
}
FORECAST{
        Maxlead = 0
}
```

```
SERIES{
	title = "LTLY"
	Format = "DateValue"
	Period = 12
	File = "d:\temp\vivaldi\10002545.DAT"
	name = "100025"
	precision = 0
	decimals = 0
}
TRANSFORM{
	Function = log
	adjust = none
	savelog=atr
}
REGRESSION{
	Variables =(
	lpyear
	)
	save = (ao ls td)
}
AUTOMDL{
	file = "\\mspv1f\Programma1\ImplSTS\Seizoen\VivX12\VIVW2K\x12\x12a.mdl"
	mode = fcst
	method = best
	Identify = first
}
ESTIMATE{
	maxiter = 999
}
FORECAST{
	Maxlead = 0
}
```

```
SERIES{
        title = "NTWW"
        Format = "DateValue"
        Period = 12
        File = "d:\temp\vivaldi\10000232.DAT"
        name = "100002"
        precision = 0
        decimals = 0
}
TRANSFORM{
        Function = none
        adjust = none
        savelog=atr
}
REGRESSION{
        Variables =(
        td1nolpyear
        )
        save = (ao ls td )

}
AUTOMDL{
        file = "\\mspv1f\Programma1\ImplSTS\Seizoen\VivX12\VIVW2K\x12\x12a.mdl"
        mode = fcst
        method = best
        Identify = first
}
ESTIMATE{
        maxiter = 999
}
FORECAST{
        Maxlead = 0
}
X11{
        mode = add
        seasonalma = msr
        sigmalim = (1.20 2.00)
save=(b1 d8 d10 d11 seasonal)
final = (ao ls)
appendfcst=yes
savelog = (m2 m7 m10 m11 q q2)
}
```

```
SERIES{
        title = "LTWW"
        Format = "DateValue"
        Period = 12
        File = "d:\temp\vivaldi\10002545.DAT"
        name = "100025"
        precision = 0
        decimals = 0
}
TRANSFORM{
        Function = log
        adjust = none
        savelog=atr
}
REGRESSION{
        Variables =(
        td1nolpyear
        )
        save = (ao ls td)
}
AUTOMDL{
        file = "\\mspv1f\Programma1\ImplSTS\Seizoen\VivX12\VIVW2K\x12\x12a.mdl"
        mode = fcst
        method = best
        Identify = first
}
ESTIMATE{
        maxiter = 999
}
FORECAST{
        Maxlead = 0
}
X11{
        mode = mult
        seasonalma = msr
        sigmalim = (1.20 2.00)
save=(b1 d8 d10 d11 seasonal)
final = (ao ls)
appendfcst=yes
savelog = (m2 m7 m10 m11 q q2)
}
```

```
SERIES{
        title = "NT6D"
        Format = "DateValue"
        Period = 12
        File = "d:\temp\vivaldi\10000232.DAT"
        name = "100002"
        precision = 0
        decimals = 0
}
TRANSFORM{
        Function = none
        adjust = none
        savelog=atr
}
REGRESSION{
        Variables =(
        tdnolpyear
        )
        save = (ao ls td )

}
AUTOMDL{
        file = "\\mspv1f\Programma1\ImplSTS\Seizoen\VivX12\VIVW2K\x12\x12a.mdl"
        mode = fcst
        method = best
        Identify = first
}
ESTIMATE{
        maxiter = 999
}
FORECAST{
        Maxlead = 0
}
X11{
        mode = add
        seasonalma = msr
        sigmalim = (1.20 2.00)
save=(b1 d8 d10 d11 seasonal)
final = (ao ls)
appendfcst=yes
savelog = (m2 m7 m10 m11 q q2)
}
```

```
SERIES{
        title = "LT6D"
        Format = "DateValue"
        Period = 12
        File = "d:\temp\vivaldi\10002545.DAT"
        name = "100025"
        precision = 0
        decimals = 0
}
TRANSFORM{
        Function = log
        adjust = none
        savelog=atr
}
REGRESSION{
        Variables =(
        tdnolpyear
        )
        save = (ao ls td)
}
AUTOMDL{
        file = "\\mspv1f\Programma1\ImplSTS\Seizoen\VivX12\VIVW2K\x12\x12a.mdl"
        mode = fcst
        method = best
        Identify = first
}
ESTIMATE{
        maxiter = 999
}
FORECAST{
        Maxlead = 0
}
X11{
        mode = mult
        seasonalma = msr
        sigmalim = (1.20 2.00)
save=(b1 d8 d10 d11 seasonal)
final = (ao ls)
appendfcst=yes
savelog = (m2 m7 m10 m11 q q2)
}
```

```
SERIES{
	title = "NTNOWD"
	Format = "DateValue"
	Period = 12
	File = "d:\temp\vivaldi\10000232.DAT"
	name = "100002"
	precision = 0
	decimals = 0
}
TRANSFORM{
	Function = none
	adjust = none
	savelog=atr
}
AUTOMDL{
	file = "\\mspv1f\Programma1\ImplSTS\Seizoen\VivX12\VIVW2K\x12\x12a.mdl"
	mode = fcst
	method = best
	Identify = first
}
ESTIMATE{
	maxiter = 999
}
FORECAST{
	Maxlead = 0
}
X11{
	mode = add
	seasonalma = msr
	sigmalim = (1.20 2.00)
save=(b1 d8 d10 d11 seasonal)
final = (ao ls)
appendfcst=yes
savelog = (m2 m7 m10 m11 q q2)
}
```

```
SERIES{
            title = "LTNOWD"
            Format = "DateValue"
            Period = 12
            File = "d:\temp\vivaldi\10002545.DAT"
            name = "100025"
            precision = 0
            decimals = 0
}
TRANSFORM{
            Function = log
            adjust = none
            savelog=atr
}
AUTOMDL{
            file = "\\mspv1f\Programma1\ImplSTS\Seizoen\VivX12\VIVW2K\x12\x12a.mdl"
            mode = fcst
            method = best
            Identify = first
}
ESTIMATE{
            maxiter = 999
}
FORECAST{
            Maxlead = 0
}
X11{
            mode = mult
            seasonalma = msr
            sigmalim = (1.20 2.00)
save=(b1 d8 d10 d11 seasonal)
final = (ao ls)
appendfcst=yes
savelog = (m2 m7 m10 m11 q q2)
}
```

Appendix F. NACE Classification

This appendix gives in Table 26 the description of the different NACE 2-digit categories used in this paper.

Table 26. Description of NACE 2-digit level.

NACE	Manufacture of
15	Food products and beverages
16	Tobacco products
17	Textiles
18	Wearing apparel
19	Leather (and products)
20	Wood (and products)
21	Paper, paperboard (and products)
22	Publishing, printing and reproduction
23	Coke, refined petroleum and nuclear fuel
24	Chemicals (and products)
25	Rubber and plastic products
26	Glass, earthenware, cement, lime and plaster articles
27	Basic metals
28	Fabricated metal products
29	Machinery and equipment
30	Office machinery and computers
31	Other electrical machinery and apparatus
32	Radio, television and communication equipment and apparatus
33	Medical, precision and optical instruments, watches and clocks
34	Motor vehicles, trailers and semi-trailers
35	Other transport equipment
36	Furniture and other manufacturing n.e.c.